# A Macro- and Microscopic Analysis of Exchange Rate Pass-through into Consumer Prices

Dissertation

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# Outline



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**Note on formatting:** In accordance with the examination regulations, the individual studies are treated as chapters within this cumulative dissertation. However, there are no specific regulations for the numbering of figures, tables, footnotes, and equations. Consequently, I decided to sequentially number them within each chapter of this dissertation, with numbering restarting at the beginning of each new chapter. This numbering scheme aims to emphasize the cumulative nature of this dissertation, in which a collection of studies is consolidated into a unified thesis. Moreover, it aims to enhance clarity and readability throughout the text.

# 1. Introduction

This cumulative dissertation comprises a collection of studies analyzing the effects of exchange rate movements on domestic prices. Accordingly, this work primarily contributes to the realm of *exchange rate pass-through* (ERPT). A pivotal feature of this dissertation is the focus on both price aggregates and individual prices for completely disaggregate products.

In the first study, *Rethinking standard metrics: the influence of effective exchange rate selection on euro area pass-through estimates*, single-authored, I examine ERPT to price aggregates in the euro area following the introduction of the euro in 1999. In this study, I employ a methodology similar to those used in policy-oriented research, which involves regressing aggregate import and consumer prices against a measure of the euro's external value alongside control variables. I challenge the conventional use of publicly available nominal effective exchange rates (NEERs) of the euro by developing alternative NEERs based on country-specific import trade flows, rather than the euro area's aggregated import and export trade flows. These newly constructed NEERs yield revised ERPT estimates to import and consumer prices of 38 percent and 18 percent after one year, respectively, marking an 8 percentage point and 7 percentage point increase over those derived from standard euro NEERs. Despite the lack of increased precision, the significant differences highlight the importance of selecting appropriate euro NEER measures for accurate ERPT estimation to aggregate prices.

In the subsequent three studies, I shift the focus from aggregate price metrics (i.e., the macroscopic perspective) to the analysis of individual prices for fully disaggregate products (i.e., the microscopic perspective), utilizing a unique scanner dataset provided by Kantar, a multinational market research firm that collects market research data globally. This dataset offers in-depth transaction data on household purchases of *fast-moving consumer goods* (FMCG), such as food, beverages, alcohol, personal care, household cleaning products, and cosmetics. FMCG purchases are significant, representing more than half of the consumer goods expenditures in many countries.

In the study titled *A microscopic analysis of UK retail price fluctuations following the Brexit vote with scanner data*, single-authored, I examine the significant depreciation of the British pound following the Brexit referendum in June 2016. This event, termed the *Brexit depreciation*, represents a rare example of an exogenous inflation shock since the outcome of the referendum came as a surprise, was not associated with macroeconomic turmoil, and since it significantly raised the prices of both imported final goods and imported intermediate goods. Hence, it resulted in a price increase across a wide range of goods, and the consequences of this inflationary shock are not confounded by fluctuations of GDP or other macroeconomic variables, justifying the use of an *event-study approach*.

The first part is targeted at the examination of inflation dynamics. Three distinct methodologies for calculating price indices are utilized: (1) Static basket with static weights, mirroring the method used by the Office for National Statistics (ONS), allows for a precise recreation of official price indices. (2) Static basket with dynamic weights maintains a consistent product set while adjusting for changes in consumer spending patterns. I show that such adjustments minimally impact inflation figures. (3) Dynamic basket with dynamic weights, which reflects both changes in product selection and consumer spending over time, captures shifts in consumer behavior and market conditions. This approach suggests that realized inflation can be much more muted when accounting for these market dynamics.

Further exploring these dynamics, the subsequent section focuses on *extensive margin adjustments*. These are price changes of newly introduced and re-appearing products, which typically command a considerable expenditure share in scanner data but tend to be overlooked in standard approaches to compute price indices. By calculating (shadow) price relatives of newly introduced and re-appearing products in relation to near-perfect substitutes or highly analogous products from the previous period, I show that extensive margin adjustments exert inflationary pressures. Notably, the analysis reveals that prices exhibited a *slight* downward movement prior to the referendum, but started to move *sharply* upward following the referendum. This implies that inflation was more pronounced than predicted by the fixed basket price indices. This result highlights the critical need for incorporating extensive margin adjustments into price index calculations.

Given the importance of extensive margin adjustments, they are integrated into the remaining sections of this study. First, I show that imported products did not become significantly more expensive than their domestically produced counterparts, a result which may initially seem paradoxical. I argue that this can be attributed to factors like the foreign share in domestically produced products or distributor and retailer pricing strategies that adjust entire price structures in response to cost shocks. Second, I show that the Brexit vote-induced depreciation shock on the Pound sterling had profound welfare and distributional implications. Although the inflationary impact was felt throughout all *social classes*, the magnitude of the impact notably varied between them. Specifically, the *Upper Middle Class* experienced the steepest price increase, and the *Working Class* a lesser, albeit still notable, increase. This suggests the *Working Class* either selected products with minimal price increases or adjusted their spending habits to circumvent some of the inflation. However, even with strategic spending shifts, they could not entirely escape the inflationary impact. Given their tighter budgets, this implies that the *Working Class* – notably major supporters of the 'Leave' campaign – were among the most impacted by the subsequent price hikes. Most alarmingly, however, is the finding that households at the lowest level of subsistence experienced high inflation (6.6 percent over the 18 months following the referendum) and thus suffered effectively the most from the Brexit vote-induced depreciation shock on the Pound sterling. A potential explanation for this observation is that consumption of the lowest income households may predominantly be targeted at the most affordable variants of essential products (i.e. for which the demand is inelastic), which implies that they have limited opportunities to switch to alternative products, even if the most affordable variants experience price increases.

Drawing on the previous study's disclosure of inflation disparities among social classes, the subsequent study titled *Anti-poor and anti-rich: Product-downgrading and the distributional effects of UK inflation in the wake of the Brexit vote*, co-authored with my doctoral supervisor Philipp Harms, as well as Guenter W. Beck and Muzammil Hussain from the University of Siegen, analyzes the distributional effects of British inflation between January 2016 and December 2017. More specifically, we investigate how different *income groups* were affected by the overall price increase. While it is well-known that effective inflation rates may differ across different parts of the population – e.g., because of group-specific expenditure shares, combined with a heterogeneous evolution of prices, or because of different abilities to alter the composition of overall spending – we focus on one particular aspect that is likely to contribute to different inflation experiences: households' ability and willingness to cushion the overall impact of the price increase by engaging in *product-downgrading*, i.e. by replacing more expensive varieties of a given product type by less expensive varieties. More specifically, we compute volume-share-weighted average unit prices for a wide range of product types and analyze whether the evolution of these averages significantly differed between income groups. The results of our analysis suggest that, when we focus on the extent of product-downgrading, the distributional consequences of the Brexit depreciation were anti-poorest and – to some extent – anti-rich: this is because the poorest households in our sample tend to purchase the most affordable varieties within narrowly defined product types, limiting their ability to further switch to more affordable varieties during the inflationary period following the Brexit referendum. In contrast, middle income-households have more flexibility to adjust their purchasing habits to evade inflation, resulting in lower inflation rates compared to the poorest households. Wealthier households, despite having the capacity to substitute away from more expensive varieties, apparently choose not to, leading them to encounter inflation rates higher than those experienced by poor households, but still below the ones experienced by poorest households. We believe that the results we present add an important insight on the distributional effects of inflation, which – for lack of appropriate data – had to be neglected so far.

The fourth and final study, *Retail prices in Latin America during the 2014-2015 US dollar rally: a microscopic perspective using scanner data*, co-authored with the same colleagues as mentioned above, relates to the finding that imported products did not significantly increase in price compared to domestically produced substitutes in the UK in 2016 and 2017. In this study, however, we focus on the *US dollar rally* that started in mid-2014, and that resulted in a substantial nominal appreciation of the US dollar against most other currencies in the world. This appreciation was driven by markets' expectations of a tighter monetary policy and accelerating growth in the US, and thus exogenous to the countries whose currencies were affected. We focus on Colombia and four other Latin American countries (Brazil, Chile, Mexico and Peru) since the overwhelming share of these countries' imports are priced in US dollars – i.e. prices of imported products should have been affected particularly strongly by the US dollar rally. We started our analysis with the expectation that the massive appreciation of the US dollar against the Colombian peso should have left its trace in Colombian retail prices, and that – at least in the short run – the prices of imported products should have moved more strongly than the prices of domestic products of the same product type. Interestingly, this is not what we find: the price reaction to the US dollar rally was delayed and muted. More specifically, it took about six months until price indices of imported products started to increase, and the mild increase in prices of a few percent pales against the depreciation of the Colombian peso against the US dollar by 40 percent. Moreover, and even more surprisingly, we find that prices of imported products and of domestic products of the same product type – i.e. domestically produced close substitutes – moved in parallel, such that the ratio of imported product prices over domestic product prices barely changed. This is also what we find for the other Latin American countries in our sample. The parallel evolution of similar imported and domestic product prices suggests a role of the retail sector that is much more active than generally believed. Moreover, due to the absence of relative price changes, we should not expect a considerable shift of consumers' spending from imported to domestic products. Our analysis of expenditure switching and quantity reactions supports this conjecture. Our research thus suggests that a better grasp of price-setting mechanics and dynamics at the retail level is crucial for understanding the effect of exchange rate fluctuations on consumer price inflation.

The rest of this dissertation outlines these four studies and concludes with a discussion that compares their key findings.

# 2. Rethinking standard metrics: the influence of effective exchange rate selection on euro area pass-through estimates

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**Abstract**

Do the import activities of France, Italy, and Ireland have an effect on import and consumer prices in Germany, Spain, and Finland? Similarly, does a country's export behavior exert an impact on its import and consumer prices? A substantial body of research on exchange rate pass-through (ERPT) to aggregate import and consumer prices in the euro area operates under these assumptions. In these studies, the nominal effective exchange rate (NEER) of the euro is constructed by weighting nominal bilateral euro exchange rates according to the aggregated export and import trade flows of the entire euro area. This is the standard practice in policy-oriented euro area ERPT estimations. However, the suitability of using such a euro NEER in ERPT analysis remains largely unresolved. Consequently, this study exploits quarterly data spanning from 1999 to 2022 to develop a variety of alternative euro NEERs. The results reveal that employing *country-specific* euro NEERs, with nominal bilateral euro exchange rates weighted solely by *import* trade flows, yields ERPT estimates for aggregate import and consumer prices that are, on average, 25 percent and 60 percent higher, respectively, compared to those obtained employing euro NEERs *not* specific to individual countries and weighting the nominal bilateral euro exchange rates according to *both* export and import trade flows. A disparity in ERPT estimates is also found at the individual country level. The findings imply that results derived from the use of publicly available euro NEERs should be interpreted with caution, since these indices are not specifically designed for ERPT analysis.

**Keywords**

Price Index, Exchange Rate Pass-through, Macro-Level Inflation Analysis, Effective Exchange Rates

**JEL-Codes**

E31 · E39 · F31 · F41 · F45

## Notational conventions

A nominal effective exchange rate (NEER) serves as a comprehensive representation of a currency's external value. It is calculated as a weighted average of a currency's nominal bilateral exchange rates with the principal trading partners of the respective country or union issuing the currency. These weights are usually derived from trade flows. In this study, the term NEER occurs in multiple contexts and variations. To ensure clarity and consistency, specific abbreviations are used for various types of NEERs:

- NEER_XI: This refers to a NEER where nominal bilateral exchange rates are weighted based on both export and import trade flows.
- NEER_I: This NEER uses nominal bilateral exchange rates weighted solely by import trade flows.

To distinguish NEERs based on country-specific trade flows, the suffix 'C' is added:

- NEER_XI_C: This denotes a NEER using nominal bilateral exchange rates weighted by country-specific export and import trade flows.
- NEER_I_C: This signifies a NEER with nominal bilateral exchange rates weighted based on country-specific import trade flows.

Accordingly, in the context of the euro area, if the NEER_XI or NEER_I abbreviation is used without the suffix 'C', it denotes a NEER calculated based on trade flows of the *entire* euro area.

## 2.1. Introduction

Quantifying the extent of exchange rate pass-through (ERPT) to aggregate prices in the euro area is important for policymakers:

*"[T]he way in which exchange rate movements pass through into import prices at the border and at the final consumer level is also critically important to understand the influence of external shocks on inflation. Consequently, understanding exchange rate pass-through into aggregate prices is vital for forecasting inflation and setting monetary policy"* (Constâncio, 2017).

In examining ERPT to aggregate prices in the euro area, studies typically estimate a simple pricing equation at the product-level, or aggregated up to the firm-, sector-, country-, or euro area-level. Within this analytical framework, prices are regressed on a measure for the exchange rate and some control variables. When considering products at various stages of production that originate from diverse origins, the exchange rate variable predominantly utilized is the nominal effective exchange rate (NEER) of the euro, i.e. a singular metric derived from a trade-weighted combination of various nominal bilateral euro exchange rates. A NEER is calculated as a weighted average of a currency's nominal bilateral exchange rates with the principal trading partners of the respective country or union issuing the currency and functions as a comprehensive representation of a currency's external value. The underlying weights are typically derived from export and import trade flows. Frequently employed euro NEERs are sourced from well-regarded institutions such as the Bank for International Settlements (BIS), the European Central Bank (ECB), and the International Monetary Fund (IMF). It follows that euro NEERs are a key element of ERPT analysis to aggregate prices in the euro area. However, it appears that no study to date has specifically addressed the choice and the impact of euro NEERs in ERPT assessments. This is a significant gap in the literature that this paper seeks to address.

What are potential pitfalls of relying on publicly available euro NEERs in ERPT analysis in the euro area? Primarily, this paper argues that the use of (i) aggregated euro area trade flows, and (ii) both export and import trade flows in the computations, make them deviate from euro NEERs specifically designed for ERPT analysis. To illustrate, consider that (i) France imports a substantial amount of maple syrup from Quebec, Canada. This premium ingredient has found its way into the French culinary tradition, being used in a variety of dishes and desserts. Now imagine that the euro depreciates against the Canadian dollar, making the maple syrup more expensive to import to France. Germany (together with all the other euro area countries), on the other hand, does not have a significant market for Quebec maple syrup, as it does not form a crucial part of its culinary traditions. Thus, why should fluctuations in the euro-Canadian dollar exchange rate influence import prices of syrups and accordingly aggregate import and consumer prices in Germany? In addition, take into account that (ii) Germany has a notable wine industry, especially white wine varieties like Riesling. Japan is a significant market for German wines. Imagine a situation where the euro appreciates considerably against the Japanese yen. This situation would make German wines pricier for

Japanese consumers, potentially reducing their demand in the Japanese market. From an ERPT perspective, the query arises why fluctuations in the euro-yen exchange rate should have an impact on Riesling prices in Germany, and correspondingly on Germany's aggregate import and consumer prices? Importantly, the issue outlined in (ii) is not specific to the euro area (or other currency unions), but carries implications for ERPT studies conducted globally.

The basic strategy adopted to identify the differential effects of euro NEERs for ERPT estimates is straightforward. Employing publicly available euro NEERs from BIS, ECB and IMF − which are typically euro NEER_XI (see notational conventions at the beginning of this study) − this research quantifies ERPT to aggregate import and consumer prices for the 10 largest euro area countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain). The analysis utilizes quarterly data spanning from 1999 to 2022, applying a distributed lag model, which is a methodology commonly applied in ERPT studies. In light of the constraints associated with utilizing publicly available euro NEERs, the subsequent analysis leverages data from the IMF's Direction of Trade Statistics (DOTS) to construct alternative euro NEERs, most importantly euro NEER_I_C versions. Distinguished from publicly available euro NEER_XI, these alternative measures are grounded on the import trade flows specific to each country, rather than aggregating import and export trade flows across the entire euro area. Following this, ERPT to aggregate import and consumer prices is re-estimated, incorporating those alternative euro NEER_I_C, and the results will be juxtaposed with the previous estimates.

The rest of this paper is structured as follows: Section 2.2. offers an overview of the aggregate exchange rate pass-through literature emphasizing the prominent role that euro NEERs play in numerous euro area ERPT studies, regardless of whether they employ aggregated or disaggregated data. Section 2.3. presents a basic micro framework for ERPT analyses utilizing NEERs. The goal is to scrutinize the appropriateness of various trade bases in the calculation of NEERs. Section 2.4. presents new reduced form aggregate ERPT estimates[1] for the euro area country sample, employing publicly available euro NEER_XI. This section further discusses the limitations inherent in the use of those NEER versions. Section 2.5. calculates and compares a variety of euro NEERs based on IMF DOTS data. Section 2.6. offers new new reduced form empirical estimates of aggregate ERPT in the euro area. In particular, these estimates are based on updated euro NEER_I_C that account for the limitations outlined in the preceding section. Section 2.7. discusses the results. Finally, Section 2.8. provides a summary and some conclusions.

## 2.2. Overview of aggregate exchange rate pass-through literature

This section seeks to contrast literature that explores ERPT to *aggregate* prices, which is particularly valuable for informing policy decisions.[2] Given the prominent role of NEERs in those studies within the euro area, it

[1] Throughout this paper, 'aggregate ERPT estimates' will be used to refer to the estimates of ERPT to aggregate import and consumer prices.

[2] Price data can be analyzed at various levels of granularity, ranging from broad product categories (e.g., food and non-alcoholic beverages or personal care) to narrower product categories (e.g., dairy products or vegetables), and further down to

is crucial to critically evaluate the specific design and construction methodology of euro NEERs.

Two distinct methodologies characterize the analysis of ERPT to aggregate prices. The primary divergence lies in the approach to aggregation. In a 'bottom-up approach', aggregate ERPT functions like a weighted average of potentially heterogeneous ERPT at a more granular stage (e.g., sectors, firms or product categories). More specifically, unit-level ERPT are identified first, and then aggregated to assess overall ERPT. This method highlights that transactions taking place at a more granular stage play a pivotal role in determining aggregate ERPT. Initial explorations of unit-level ERPT were primarily grounded in the trade literature and utilized sector-level data (i.e. sectors as units). Goldberg & Knetter (1997) provide an excellent survey on early ERPT studies based on disaggregated data. The 'Campa-Goldberg compositional-trade hypothesis' (Cheikh & Rault, 2017, p.3) underscores the necessity of employing micro-level data to shed light on specific characteristics of ERPT. This hypothesis posits that the observed reduction in ERPT to import prices in various OECD nations over recent years can be primarily attributed to shifts in import compositions. Specifically, there has been a transition towards products that exhibit a lesser sensitivity to exchange rate fluctuations, such as differentiated goods in the manufacturing sector. Conversely, the 'top-down approach' takes a different route, where prices and bilateral exchange rates are aggregated first, followed by the determination of ERPT. Early studies in this field, such as those by Bailliu & Fujii (2004), Campa & Goldberg (2005) and McCarthy (2007) have received significant attention. Cheikh & Rault (2017) propose that macroeconomic factors, like the inflation environment, play a crucial role in explaining ERPT. Consequently, it becomes imperative for policymakers to consider both macro- and microeconomic facets when evaluating the extent of ERPT. However, irrespective of the methodology employed – be it the 'bottom-up' or the 'top-down' approach – there appears to be a consensus that ERPT to aggregate import prices is incomplete, yet significantly more pronounced than ERPT to consumer prices.

A pervasive observation when utilizing disaggregated data is the heterogeneity of ERPT across units. For instance, as pointed out by Burstein & Gopinath (2014, p.403), "ERPT estimates exhibit substantial variance across different goods." This variation inherently suggests that top-down approaches may be prone to 'aggregation bias', a phenomenon well-documented in the macroeconomic literature. This kind of bias is theoretically formulated by Pesaran & Smith (1995), who illustrate that aggregation can potentially induce an upward bias in estimates derived from heterogeneous panels. This rationale is also adopted by Imbs et al. (2005) in their efforts to explain the purchasing power parity puzzle. Furthermore, Mumtaz & Oomen & Wang (2011) show that top-down approaches in ERPT studies are not immune to the aggregation bias. Their study, which encompasses an analysis of the United Kingdom's import prices at both aggregate and industry levels, reveals a significant upward bias in long-run ERPT when inferred from aggregate data.

This significant limitation naturally leads one to question the continued use of top-down approaches. Top-

specific product types within these categories (e.g., cheese), individual products (e.g., gouda cheese), or even specific items (e.g., a particular brand of gouda cheese identified by a unique product code). While some studies delve into ERPT analysis at the item or product level, this paper focuses on research that examines ERPT to prices at a higher degree of aggregation. Such studies are particularly valuable for informing policy decisions. Conversely, dissecting ERPT at the product or item level constitutes a significant aspect of academic research.

down approaches persist primarily due to the practical advantages they offer. First and foremost, they benefit from the extensive availability of aggregate data, which is typically more readily accessible and covers a longer historical timeframe. This allows for a comprehensive analysis of long-term trends without the need for the time-consuming data collection phases often associated with bottom-up approaches. In addition, the broad availability of aggregate data simplifies cross-country comparisons by utilizing standardized data categories. As highlighted by Shambaugh (2008, p.561), "Micro-level studies of a particular product or industry [..] limit the ability for international comparisons due to lack of data availability". This feature not only enables an international analysis but the aggregated data also harmonizes well with other macroeconomic variables, enabling a comprehensive analysis of economic dynamics. Moreover, utilizing aggregated data, top-down approaches directly offer a macroscopic view of broader economic trends. This wide-angle perspective often aligns more closely with the policymakers' interest in understanding and addressing general market dynamics. Finally, aggregate data has the potential to mitigate the noise inherent in micro-level data. This noise could stem from a variety of sources including smaller sample sizes, short-term variations, or other factors that might not be as evident or influential when examining data at a larger, more aggregate level. Corroborating this, Kenny & Mcgettigan (1998, p.1148) state, "The partial nature of disaggregated studies means that findings of incomplete PT [pass-through], while very interesting in themselves, should not be adduced as evidence that this result carries over to the broader macroeconomy."

The pivotal question regarding the relevance of this research is to ascertain whether NEERs are commonly utilized in ERPT analyses. Having established that both bottom-up and top-down approaches are prevalent, it is crucial to determine whether NEERs hold a substantial influence within any of the approaches.

In bottom-up approaches with specific items as the units of analysis, the specific exchange rate between the importer and exporter economies typically serves as the main explanatory variable. Consequently, the NEER does not play a role in these studies. At the firm level, the complexity increases when accounting for imports from diverse origins. Accordingly, multiple importer-exporter exchange rates need to be combined into a single exchange rate variable (like the NEER). Alternatively, transactions might be grouped into origin-specific, firm-level observations to identify a single bilateral exchange rate variable for each observation. Likewise, in analyses utilizing sector-specific data, imports typically stem from different origins. Thus, transactions might be grouped into origin-specific, sector-level observations, or multiple importer-exporter exchange rates need to be combined into a NEER (as, e.g., conducted by Campa & Mínguez, 2006, Bandt & Razafindrabe, 2014, Cheikh & Rault, 2017, or Osbat & Sun & Wagner, 2021). This points towards a considerable influence of the NEER in bottom-up approaches to ERPT.

In top-down approaches, the categorization by the origin of goods can also be a distinct feature. Nevertheless, this strategy requires comprehensive micro-level data since it necessitates deriving country pair-specific price indices from product-, firm-, or sector-level data. Given that such detailed data is rarely available, only a few studies have managed to integrate country pair-specific price indices into aggregate analysis, with the work of Gopinath et al. (2020) standing out as a notable example. In this study, Gopinath and colleagues use import unit values detailed at the HS 6-digit product level to compute aggregated Fisher price indices at the bilateral country level, applying a distributed lag model across a large set of advanced and emerging economies. They regress the bilateral price indices on the countries' bilateral exchange rate, alongside the importer's dollar exchange rate and an interaction term incorporating both the bilateral and dollar exchange rates and the importing country's dollar invoicing share. Their findings indicate a nearly full pass-through at a one-year horizon, with the dollar exchange rate absorbing most of the effect. Furthermore, they find that a larger dollar invoicing share corresponds to a higher degree of dollar pass-through.

When leveraging aggregate data in top-down approaches, however, the dominant strategy is to employ NEERs as explanatory variable (in the euro area context, see e.g., Schröder & Hüfner, 2002, Hahn, 2003, Faruqee, 2006, Landolfo, 2007, Shambaugh, 2008, Gaggl, 2009, Misztal, 2010, Burstein & Gopinath, 2014, Comunale, 2015, Özyurt, 2016, Comunale & Kunovac, 2017, Georgiadis & Gräb & Khalil, 2020, Colavecchio & Rubene, 2020, Ortega & Osbat, 2020, or Arsova, 2021). Appendix A reviews studies that explore aggregate ERPT to import and consumer prices in the euro area, with a particular focus on the temporal and geographical scope, the type of NEER utilized, the model specifications, and some main findings.

Table 1 presents a comprehensive summary of the 19 aforementioned studies that investigate ERPT to import and consumer prices in the euro area, employing NEERs as exchange rate variable. It is clearly evident from the table that several studies examining country-specific price indices opt to incorporate a euro NEER that is not country-specific in their analysis. Furthermore, a notable majority, specifically 17 out of the 19 studies, favors the use of euro NEERs where nominal bilateral exchange rates are weighted based on both export and import trade flows, as opposed to their solely import-weighted counterparts. These observations hold regardless of whether the studies employ disaggregated price data (aligning with a bottom-up approach) or aggregated price data (aligning with a top-down approach). These preferences are somewhat unexpected, given the diverse trade behaviors observed across euro area countries and the claim that a euro NEER, where nominal bilateral exchange rates are weighted solely by import trade flows, would be more appropriate in the analysis of ERPT to import and consumer prices, as put forward by Colavecchio & Rubene (2020, p.9): "Second, we have to choose between country import weights or export weights. We choose the import-weighted NEER as our measure, since we think that it is more appropriate when analysing import and consumer prices."

While Fidora & Schmitz (2020) assert that the ECB's euro NEER, where nominal bilateral exchange rates are weighted based on euro area-wide export and import trade flows, serve as "a summary measure of a currency's external value" (p.5), it is critical to acknowledge that this metric may be of limited use to assess transactions at the product level. On this granular stage, the invoicing currency plays a key role in determining the extent of ERPT (Bandt & Razafindrabe, 2014).[3] In the context of the euro area, it is

[3]Beyond the considerations influencing the selection of a specific currency for price-setting, contemporary research is increasingly centered on the connection between ERPT and currency invoicing. This topic has been brought to the forefront due to the availability of corresponding micro-data, as highlighted in the study such by Gopinath & Itskhoki & Rigobon (2010). For example, Bonadio & Fischer & Sauré (2019) demonstrate that ERPT is complete (equal to one) for goods invoiced in euros the day following the significant appreciation of the Swiss franc on January 15, 2015. Although a NEER that weights nominal bilateral exchange rates based on invoicing patterns might offer better insights for ERPT than one based on trade flows, such

not inherently evident why aggregated euro area trade flows would offer a more accurate representation of invoicing patterns compared to country-specific trade patterns. Furthermore, it remains open to discussion whether export relationships hold any significance in this context, or if import relationships offer a more accurate depiction of invoicing patterns.

More generally, the application of NEERs extends far beyond their role in ERPT analyses. It is vital, therefore, to consider whether the underlying aggregation procedures are adeptly suited for analyses in diverse fields such as macroeconomics, monetary policy, trade policy, and international investment analyses.

data is rarely available on a comprehensive scale and thus not a part of this study.

Table 1: Overview of euro area ERPT studies incorporating euro NEERs

| | | | | NEER | | | |
|---|---|---|---|---|---|---|---|
| **Study** | **Euro area countries** | **Sample period** | **Lowest price data level** | **Country-specific or euro-area wide?** | **Weighted based on X and I, or solely I?** | **Computed against all trade partners or partners outside the euro area?** | **Source** |
| Schröder & Hüfner (2002) | 5 | 1981-2001 | Country-level | Country-specific | Exports and imports | All trade partners | Bank of England |
| Hahn (2003) | Euro area | 1970-2002 | Euro area-level | Euro area wide | Exports and imports | Partners outside the euro area (narrow group of countries) | ECB |
| Faruqee (2006) | Euro area | 1990-2002 | Euro area-level | Euro area wide | Exports and imports | Partners outside the euro area (narrow group of countries) | ECB |
| Campa & Mínguez (2006) | 12 | 1989-2001 | Sector-level | Country-specific | Solely Imports | Partners outside the euro area (five major non-euro area partners) | Own calculations |
| Landolfo (2007) | Euro area | 1970-2003 | Euro area-level | Euro area wide* | Exports and imports* | Partners outside the euro area (narrow group of countries*) | ECB |
| Shambaugh (2008) | 2 | 1973-1999 | Country-level | Country-specific | Exports and imports | All trade partners | IMF IFS |
| Gaggl (2009) | 5 | 2000-2007 | Country-level | Country-specific | Exports and imports | All trade partners | Eurostat |
| Misztal (2010) | Euro area | 1998-2007 | Euro area-level | Euro area wide | Exports and imports* | Partners outside the euro area* | / |
| Burstein & Gopinath (2014) | 3 | 1975-2011 | Country-level | Country-specific | Exports and imports | All trade partners | BIS |
| Bandt & Razafindrabe (2014) | 5 | 2005-2013 | Sector-level | Euro area wide | Solely imports | Partners outside the euro area (US, UK and China) | Own calculations |
| Comunale (2015) | 19 | 1994–2014 | Country-level | Euro area wide | Exports and imports | Partners outside the euro area (broad group of countries) | Eurostat |
| Özyurt (2016) | 5 | 1996-2015 | Country-level | Euro area wide | Exports and imports | Partners outside the euro area (broad group of countries) | ECB |
| Cheikh & Rault (2017) | 12 | 1990-2013 | Sector-level | Country-specific | Exports and imports | All trade partners | IMF IFS |
| Comunale & Kunovac (2017) | 4 | 1992-2016 | Country-level | Country-specific | Exports and imports | All trade partners | OECD |
| Georgiadis & Gräb & Khalil (2020) | 10 | 1995-2014 | Country-level | Country-specific | Exports and imports | All trade partners | IMF IFS |
| Colavecchio & Rubene (2020) | 19 | 1997–2019 | Country-level | Euro area wide | Solely imports | Partners outside the euro area (broad group of countries) | BIS |
| Ortega & Osbat (2020) | 19 | Late 1990s-2019 | Country-level | Country-specific | Exports and imports | Partners outside the euro area | Own calculations |
| Osbat & Sun & Wagner (2021) | Euro area | 2000-2020* | Sector-level | Euro area wide | Exports and imports | Partners outside the euro area (broad group of countries) | ECB |
| Arsova (2021) | 11 | 1999–2018 | Country-level | Country-specific | Exports and imports | All trade partners | IMF IFS |

**Note:** This table depicts the use of euro NEERs in various ERPT studies targeting the euro area and/or its individual member countries. The initial column cites the corresponding study. Subsequent columns provide the following information: the second delineates the geographic focus of the analysis – the euro area as a whole or its individual member countries –, the third outlines the study's sample period, and the fourth indicates the data granularity, differentiating between aggregate and disaggregate levels at the most granular stage. Columns five to eight assess the specific euro NEER applied in each study, detailing its geographic scope (euro area-wide or country-specific), nominal bilateral euro exchange rates weighting basis (export and import trade flows or solely import trade flows), range of trading partners considered (all or those outside the euro area), and the original source of the euro NEER data. Instances where details could not be clearly ascertained from the study are marked with an asterisk (*), indicating a guess.

## 2.3. A basic micro framework for ERPT analyses with NEERs

Numerous ERPT studies rely on a NEER as the exchange rate variable in their regression models (see Table 1 for an overview in the euro area context). Consequently, the NEER – a singular metric derived from a trade-weighted combination of various exchange rates – serves as the key explanatory variable in a significant portion of empirical ERPT assessments. However, the computation of the NEER is an aspect that often lacks proper consideration in those studies. Instead, publicly available NEERs from the BIS, ECB and IMF and other institutions are typically utilized, implicitly assumed to fulfill the requisites of ERPT analyses. Nonetheless, these NEERs are not specifically designed for ERPT analysis. This section intends to explore a weighting scheme that can more accurately capture the influence of NEER variations on aggregate price fluctuations.

Conceptually, the basis for reduced-form econometric specifications employed to estimate ERPT to aggregate import prices typically starts by describing the pricing behaviour of foreign exporting firms, as in Dornbusch (1987) or Bailliu & Fujii (2004). In line with those models, a foreign firm exporting a good to the domestic market faces a static profit-maximization problem represented as:

$$\max_{\hat{p}} \pi = \hat{p}q - C(q) \tag{1}$$

where $\pi$ denotes profits in foreign currency, $\hat{p}$ is the price of the good in the foreign currency, $q$ is the quantity demanded for the good, and $C(.)$ is the cost function in foreign currency. The price of the good in the foreign currency $\hat{p}$ relates to the price of the good in the domestic currency $p$ as:

$$\hat{p} = s^{-1}p \tag{2}$$

where $s$ is the bilateral nominal exchange rate with the foreign currency as base currency. Accordingly, when the foreign firm sets the price of the good in its own currency, akin to producer currency pricing, the price of the good in domestic currency mechanically reacts to a change in the bilateral nominal exchange rate.

Solving the optimization problem implies the following relationship between the price of the good in domestic currency and the bilateral nominal exchange rate:

$$p = sC_q\mu \tag{3}$$

where $C_q$ is the marginal cost and $\mu$ is the markup for the foreign exporting firm of price over marginal cost defined as $\mu \equiv \eta/(\eta - 1)$, with $\eta$ being the price elasticity of demand for the good.

This expression highlights that the price of the good in the domestic currency is determined by the bilateral nominal exchange rate, the foreign exporting firm's marginal cost and the foreign exporting firm's markup. Thus, it is important to take into account the foreign exporting firm's marginal cost and markup to isolate the relationship between the price of the good in domestic currency and the bilateral nominal exchange rate.

Following this framework, empirical estimations of ERPT to individual goods import prices may employ log-linear, reduced-form equations of the form:

$$p_t = \alpha + \lambda s_t + \tau w_t + \eta y_t + \epsilon_t \tag{4}$$

where $w_t$ and $y_t$ measure the foreign exporting firm's marginal cost and the importing country's demand conditions, respectively, with the latter serving as a proxy for the markup. Upon determining the ERPT to the prices of individual imported goods, these estimates can be aggregated to ascertain the overall ERPT, illustrating a bottom-up approach in ERPT analysis.

Specification (4) can be adapted for directly estimating ERPT for aggregate import prices, provided that bilateral nominal exchange rates and foreign exporting firms' marginal costs are being aggregated as well. This method characterizes the top-down approach to ERPT. However, a key assumption of regression models is the stationarity of data. For aggregate price levels and aggregated/effective exchange rates, it is not always certain whether these time series oscillate around a fixed mean or have a tendency to wander over time, suggesting a non-stationary process. Given that these series are often found to be best described as integrated of order one (Bailliu & Fujii, 2004), an approach to ensuring stationarity is to use first differences in estimating the ERPT equation, i.e., using period-on-period log changes – or growth rates – instead of levels. This adjustment helps avoid issues related to non-stationarity and spurious regression, resulting in more reliable estimates. In addition, it is common to include lags of the explanatory variables to account for the observed inertial behaviour of inflation. Consequently, when using the output gap to account for changes in domestic demand conditions, the resulting ERPT equation involving aggregate import price growth rates and NEER growth rates becomes:

$$\Delta\bar{p}_t = \alpha + \sum_{j=0}^{J} \lambda_j \Delta\bar{s}_{t-j} + \sum_{k=0}^{K} \tau_k \bar{w}_{t-k} + \sum_{l=0}^{L} \eta_l y_{t-l} + \epsilon_t \tag{5}$$

In this equation, $\Delta$ denotes the period-on-period growth rate and the bar over the variables signifies an aggregate measure.

A crucial question arises when considering this ERPT equation to aggregate import prices: How should nominal bilateral exchange rates be aggregated in order to accurately estimate the effect of NEER movements on aggregate import price movements? Notably, shifts in the domestic currency import price of individual goods, driven by variations in the bilateral nominal exchange rate, are determined by the behavior of *foreign exporting firms.* They do *not* depend on the exporting activities of the domestic country. As such, it appears appropriate to weight nominal bilateral exchange rate changes according to the import relationships of the domestic country. In other words, assigning higher weight to exchange rate changes with trade partners from which the country imports more heavily yields a more accurate representation of the effect of NEER movements on aggregate price fluctuations than exploiting export and import trade relationships.

Given this simple analytical framework, it is surprising that Bailliu & Fujii (2004) and many other studies exploit NEERs that are based on export and import trade flows, and do not compute and exploit NEERs that are solely based on import trade flows, when estimating ERPT to aggregate import prices. Moreover, it is striking that, in the euro area context, the euro NEER utilized is typically not tailored to individual euro area member countries, but instead is derived from aggregate euro area trade volumes. This lack of specificity fails to account for distinct trade patterns of individual euro area countries. This study addresses these two shortcomings by incorporating country-specific NEERs, with nominal bilateral exchange rates weighted based on import trade flows, in ERPT estimates for aggregate import prices in the euro area.

Equation (5) can also be used to estimate ERPT to aggregate consumer prices encompassing both, consumer prices of domestically produced and imported goods. In this context, ERPT will be influenced by an array of factors such as ERPT to import prices, the proportion of imports in aggregate consumer prices, the response of prices of domestically produced goods to exchange rate fluctuations, local distribution costs (including transportation, marketing, and other services) and pricing strategies adopted by wholesalers and retailers. Generally, ERPT to aggregate consumer prices is expected to be smaller than that to aggregate import prices. However, it is important to note that it is not necessarily proportional to the share of imports in the consumption basket.

In the case of ERPT to aggregate consumer prices, it is less clear-cut whether NEERs that are based on import trade flows are superior to NEERs that are based on total trade flows. There are several reasons why the exporting activities of the domestic country might also be relevant for ERPT to aggregate consumer prices. For example, variations in the exchange rate may impact the competitiveness of domestic firms. An appreciation of the domestic currency can make exported goods more expensive in international markets, potentially reducing demand for these goods. As a result, the domestic supply could increase, exerting downward pressure on consumer prices. In addition, pricing to market behavior, where exporters adjust their export prices according to market conditions in the importing country, could also play a role. When the domestic currency appreciates, domestic firms exporting goods might choose to absorb some or all of the exchange rate changes into their profit margins, rather than passing on the increased costs to consumers in the foreign market. This strategy helps maintain their market shares abroad, but also affects the domestic value and profitability of exports. If a currency appreciation makes foreign earnings less valuable, domestic firms may seek to compensate for the reduced profitability by increasing domestic prices. Nevertheless, even with these factors taken into account, it is likely that NEERs based on import trade flows still offer a more accurate reflection of the exchange rate's impact on aggregate consumer prices. This is because the direct effects stemming from import prices may overshadow the indirect effects mediated through export relationships. In other words, given the immediate and tangible effect exchange rate movements have on import prices, and subsequently on consumer prices, the import-weighted approach might capture the dynamics of ERPT more accurately.[4]

Finally, it is important to highlight two extreme scenarios where the basis on which NEERs are calculated – whether it is export and import or solely import trade flows – would have no or bearing on the results. First, this would be the case when a country's import and export relationships are identical, meaning that the trade volumes and partners coincide for both import and export activities.[5] Second, the specifics of the trade relationship would not influence the NEER when the currency of a country appreciates or depreciates uniformly against all other foreign currencies, as the effect would be universally equal. However, these scenarios are idealized and rarely, if ever, match the complexity and asymmetry of real-world trade relationships. The greater the deviation of a country's trade patterns from these extreme scenarios – that is, the more asymmetrical the import and export relationships, or the more varied the currency movements against different trading partners are – the more crucial it becomes to carefully consider the trade base of the NEER computation. In these more realistic circumstances, the choice of the NEER could have a significant bearing on the magnitude and accuracy of aggregate ERPT estimates.

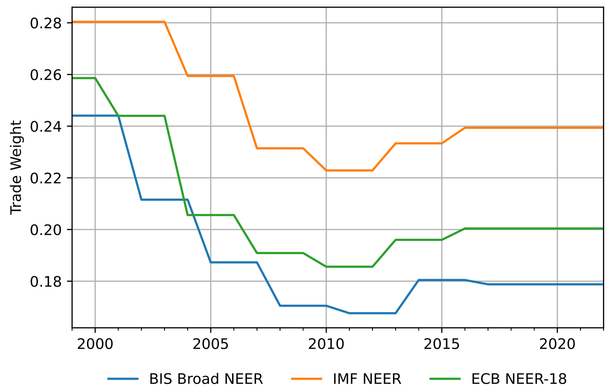
## 2.4. New reduced form empirical estimates of aggregate ERPT in the euro area

ERPT to aggregate import or consumer prices of the euro area or individual euro area countries is frequently estimated using a euro NEER_XI that is publicly available from sources such as the BIS, ECB, or IMF. Even though these studies usually incorporate country-specific import or consumer prices, the euro NEER employed is often computed for the entire euro area. There are some differences in the methodologies used by the BIS, ECB, and IMF to calculate the trade weights for their euro NEER_XI, leading to variations in the resulting trade weights (see Tables 9 to 11 in Appendix C for an overview of the trade weights computed by these organizations). Figure 1 graphically illustrates the variation in trade weights over time concerning the euro area's two key trading partners: The United States and China. Over the past several decades, China's prominence as a trading partner for the euro area has steadily increased. Conversely, the United States' role weakened until mid-2010s before experiencing a slight resurgence. These trends are reflected in all three euro NEER_XI, although their levels vary. For instance, the most recent trade weight for China (the United States) is 0.18 (0.20), 0.24 (0.18), and 0.24 (0.24) according to the ECB, BIS, and IMF, respectively. Despite these differences in levels, the quarter-on-quarter growth rates in these euro NEER_XI exhibit a high degree of correlation (as shown in Table 2) and the euro NEER_XI indices move very closely to each other (as shown in Figure 2). These observations suggest that aggregate ERPT estimates may not be significantly sensitive to the specific choice of the publicly available euro NEER_XI.

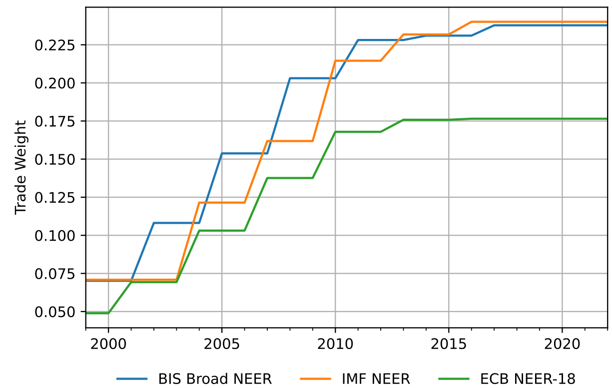
[4]Further theoretical investigation is needed to determine whether this hypothesis holds true, considering the complexity and multifaceted nature of ERPT determinants. This, however, falls beyond the scope of this paper.

[5]Note that this does not necessarily hold true if trade weights also capture 'third market effects', i.e. the competition faced by exporters from local producers and foreign countries' exporters in the economies of the export destination.

Figure 1: Variation in trade weights of the United States and China underlying publicly available euro NEER_XI




(a) United States




(b) China

**Note:** This figure presents the trade weights of the United States and China that underlie the euro NEER_XI as reported by the ECB, BIS, and IMF. To facilitate comparison, the BIS and IMF trade weights have been adjusted to total one over the 18 partner countries as defined by the ECB in its NEER-18 (see Appendix C for further details).

Table 2: Correlation matrix of publicly available euro NEER_XI quarter-on-quarter growth rates

| | BIS Broad NEER | ECB NEER-18 | IMF NEER |
|---|---|---|---|
| BIS Broad NEER | 1 | 0.979 | 0.996 |
| ECB NEER-18 | 0.979 | 1 | 0.971 |
| IMF NEER | 0.996 | 0.971 | 1 |

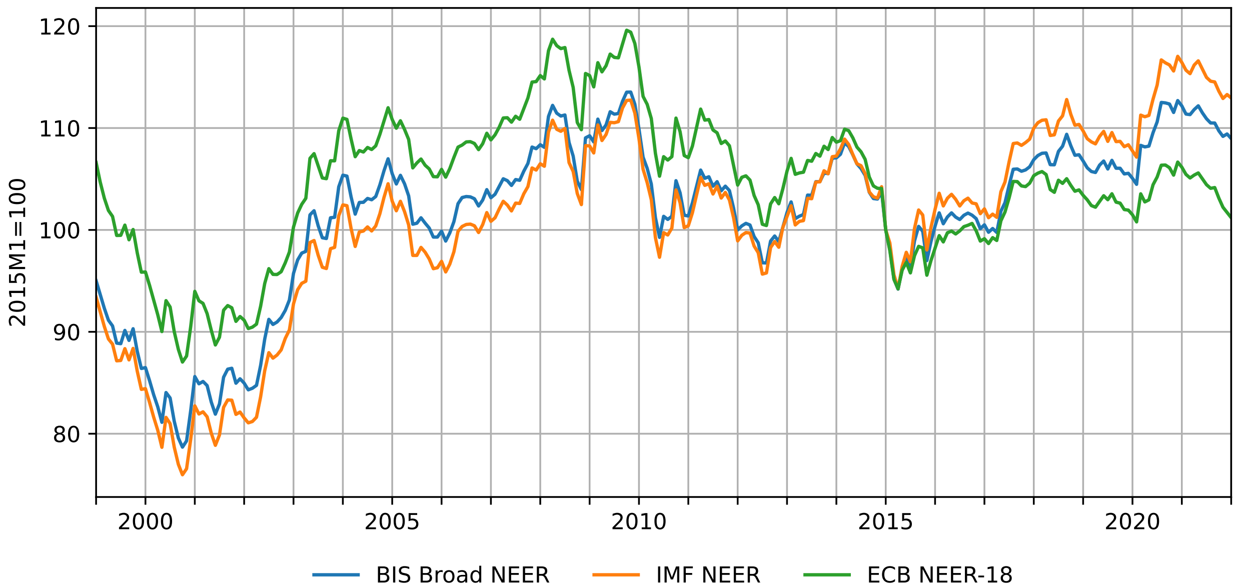
**Note:** This table depicts the correlation matrix of selected publicly available euro NEER_XI quarter-on-quarter growth rates from 1999Q1 to 2022Q4.

In order to test this conjecture, a distributed lag model closely related to equation (5) is constructed. Distributed lag models are a popular choice for ERPT estimations, as illustrated by studies such as Burstein & Gopinath (2014), Comunale (2015), Özyurt (2016) or Gopinath et al. (2020). This study's specification employs period-on-period growth rates for aggregate prices and effective exchange rates instead of levels. It incorporates the output gap to account for changes in domestic demand conditions, and changes in the trade-weighted producer price index to account for external price pressures. The model also includes lags of the explanatory variables to capture the observed inertial behaviour of inflation. Furthermore, the model accounts for the inclusion of the 10 largest euro area countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain) through a panel structure, as follows:

$$\Delta Price_{j,t} = \alpha_0 + \sum_{k=0}^{4} \beta_k \Delta NEER_{t-k} + \sum_{k=0}^{4} \eta_k Output\_Gap_{j,t-k} + \sum_{k=0}^{4} \gamma_k Foreign\_PPI\_YoY_{t-k} + \mu_j + \epsilon_{j,t} \quad (6)$$

where $\Delta Price_{j,t}$ represents the quarterly growth rate in the aggregate price measure of euro area country $j$ at time $t$, while $\Delta NEER_{t-k}$ signifies the quarterly growth rate in the euro NEER_XI at time $t-k$. The variable

Figure 2: Publicly available euro NEER_XI indices




$Output\_Gap_{j,t-k}$ stands for the output gap of euro area country $j$ at time $t-k$ while $Foreign\_PPI\_YoY_{t-k}$ designates the trade-weighted annual growth rate in foreign PPI for the euro area at time $t$. The term $\mu_j$ represents country-specific fixed effects. The residual $\epsilon_{j,t}$ captures the variation in the growth rate in aggregate prices for euro area country $j$ that is not explained by the euro NEER_XI or control variables, and $\alpha_0$ serves as the intercept of the model.

The $\beta_k$ coefficients illustrate the average influence of the $k$-th lagged euro NEER_XI growth rate on the current quarter's growth rate in aggregate prices. Note that throughout this paper, all NEERs are constructed such that an increase stands for an appreciation of the domestic currency. By including four lagged euro NEER_XI variables, the model seeks to understand the relationship between euro NEER_XI changes and aggregate price changes at different quarterly horizons within a year. As stated by Colavecchio & Rubene (2020), this reduced-form equation, which incorporates controls for domestic economic slack and external price pressures, provides a measure of inflation sensitivity to exchange rate fluctuations without attributing any structural interpretation. Consequently, what is referred to in this context as ERPT represents a correlation between effective exchange rate changes and aggregate price changes (both expressed as growth rates).

The data span from the first quarter of 1999 to the fourth quarter of 2022. Due to the use of quarter-on-quarter growth rates, the first quarter of 1999 is dropped from the analysis. Given that the dataset includes 10 countries, each with 24 years of data divided into quarters, there are potentially 950 observations. However, due to the four quarterly lags, 40 observations – corresponding to one year's worth of data across all 10 countries – are removed from the analysis.

The variables employed in this analysis are as follows: $Price_{j,t}$ is either defined as the imports deflator for aggregate import prices, or goods HICP for aggregate consumer prices. The key explanatory variables used in this analysis include the euro NEER_XI from the BIS (broad NEER), ECB (against 18 trading partners, i.e. ECB NEER-18), and IMF. The output gap, a representation of domestic economic slack, is derived from real GDP (seasonally adjusted). It is calculated using the Hodrick-Prescott (HP) filter with a smoothing parameter lambda of 1,600, which is a standard choice for quarterly data as noted by Comunale (2015). External price pressures are quantified by the quarterly trade-weighted producer price index (PPI) growth rate, compared to the same quarter of the previous year. This is calculated as:

$$Foreign\_PPI\_YoY_t = \sum_{i=1}^{N=18} PPI\_YoY_{i,t} \times w_{i,t} \tag{7}$$

In this equation, $PPI\_YoY_{i,t}$ represents the quarterly year-on-year growth rate in the PPI of the euro area's $i$-th trade partner at time $t$. The variable $w_{i,t}$ corresponds to the weight allocated to that $i$-th trade partner of the euro area at time $t$. The weights for all $N$ trade partners sum to one at time $t$ and are outlined in Tables 9 to 11 in Appendix C. Note that the number of trade partners, $N$, is restricted to 18 – aligning with the ECB's set of partner countries for its NEER-18 calculation – due to the limited availability of PPI data. These 18 trade partners consist of the ECB NEER-12 group of partner countries: Australia, Canada, Denmark, Hong Kong, Japan, Rep. of Korea, Norway, Singapore, Sweden, Switzerland, United Kingdom, United States + Bulgaria, China, Czech Rep., Hungary, Poland and Romania. Further details on country groups, sources and definitions of variables can be found in Appendix B.

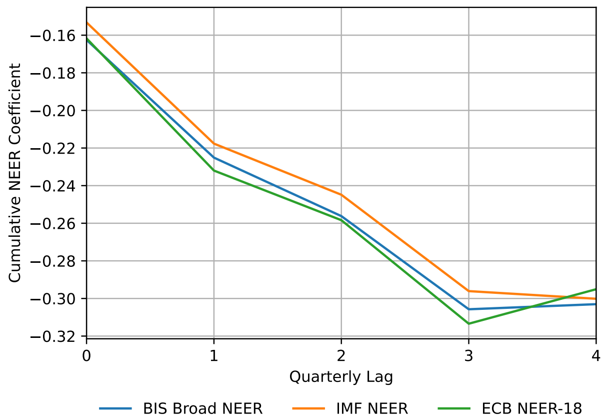
Figure 3 portrays ERPT to both aggregate import and consumer prices across varying time horizons within a year. Detailed regression results are depicted in Tables 3 and 4. It can be observed that ERPT to both import and consumer prices amplifies over the time horizon. After one year, ERPT to consumer prices is roughly one-third of ERPT to import prices, confirming that ERPT is notably higher for import prices than for consumer prices. With a value around 30 percent, ERPT to import prices skews towards the lower band of those reported in the literature. ERPT to consumer prices, with a value of 10 to 12 percent, marginally exceeds the average values typically reported in existing literature.[6] Finally, ERPT to aggregate prices after one year for the euro area countries in the sample is illustrated in Figure 4.

Given the theoretical consideration in Section 2.3., it is important to reflect upon the accuracy of these estimates. Several factors should be highlighted in this context.

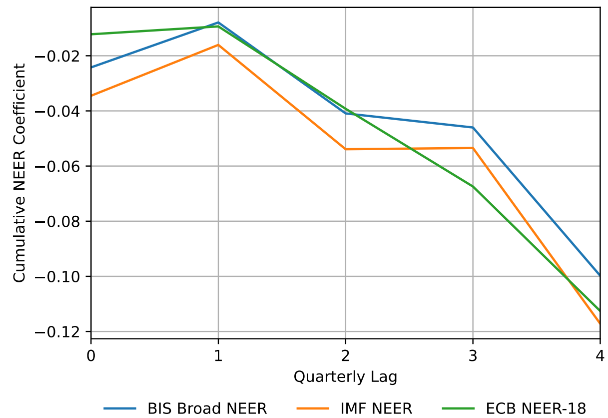
First, IMF DOTS reveals significant heterogeneity in the trade patterns across individual euro area countries. This heterogeneity is illustrated in Figure 5, which depicts the total trade shares of the sample

[6] Upon closer examination, it is evident that the introduction of control variables enhances the explanatory power of the model significantly. When employing the ECB's euro NEER_XI as the exchange rate variable, the model's capability to explain variability improves markedly with the inclusion of the output gap and foreign PPI. The R-Squared value – a metric that quantifies the model's explanatory power – amplifies this observation. Specifically, for import prices, the R-Squared value rises from about 8 percent to 59 percent. Similarly, for consumer prices, the value rises from 1 percent to 25 percent. Thus, the inclusion of these controls helps establish a more comprehensive understanding of the factors driving aggregate price fluctuations in the euro area.

Figure 3: Dynamics of ERPT to aggregate prices using publicly available euro NEER_XI




(a) Import deflator




(b) HICP

**Note:** This figure depicts the cumulative sum of the $\beta_k$ coefficients from equation (6). Note that all NEERs are defined in such a way that an increase represents an appreciation of the domestic currency. By using four lags, the model shows the relationship between NEER_XI quarter-on-quarter growth rates and aggregate price quarter-on-quarter growth rates at different horizons within a year. At the annual horizon, this empirical evidence suggests that a 1 percent nominal effective depreciation in the euro raises aggregate import (consumer) prices by, on average, 0.30 (0.10-0.12) percent.

countries with the United States and China over time. These total trade shares are computed as follows:

$$z_{ij,t} = \frac{M_{ji,t} + X_{ji,t}}{\sum_{i=1}^{N=18}(M_{ji,t} + X_{ji,t})} \tag{8}$$

Here, the variable $z_{ij,t}$ is defined as the total trade share between a non-euro area country $i$ and a euro area country $j$ in period $t$. The import value of euro area country $j$ from country $i$ in period $t$ is denoted as $M_{ji,t}$, which can also be interpreted as the export value from non-euro area country $i$ to euro area country $j$ during the same period. On the other hand, $X_{ji,t}$ symbolizes the export value from the euro area country $j$ to country $i$ at period $t$. To compute $z_{ij,t}$, the sum of the imports of country $j$ from $i$ and the sum of the exports from $j$ to $i$ is taken and then divided by the total trade activity between the euro area country $j$ and all its 18 partner countries during period $t$. This total trade activity is represented by the summation term in the denominator, $\sum_{i=1}^{N=18}(M_{ji,t} + X_{ji,t})$. The parameter $N$ is fixed at 18, aligning with the defined set of partner countries used in the ECB NEER-18 calculation. Data is aggregated on an annual basis so that $t$ refers to years. Therefore, for every euro area country $j$, the trade share $z_{ij,t}$ sums up to one over the 18 partner countries $i$ for each year $t$ ranging from 1999 to 2022.

The graph shows that aggregated euro area trade shares can mask the specific importance of particular trading partners for individual countries within the euro area. Take the case of the United States: As of 2022, its trade share amounts to 12 percent for both Finland and Austria, whereas for Italy and Portugal, the figure stands at 24 percent. Ireland's trade share with the United States is particularly high, exceeding 40 percent. With respect to China's trade share in 2022, the figures vary from 11 percent for both Austria

Table 3: Estimation results of ERPT to aggregate import prices using publicly available euro NEER_XI

| | Dependent Variable: Import Deflator | | |
|---|---|---|---|
| | BIS Broad NEER | ECB NEER-18 | IMF NEER |
| Constant | -0.001** | -0.002*** | -0.001 |
| | (0.000) | (0.001) | (0.000) |
| NEER | -0.163*** | -0.162*** | -0.153*** |
| | (0.034) | (0.035) | (0.030) |
| NEER Lag 1 | -0.063*** | -0.070*** | -0.064*** |
| | (0.021) | (0.025) | (0.018) |
| NEER Lag 2 | -0.031*** | -0.026* | -0.027** |
| | (0.012) | (0.014) | (0.011) |
| NEER Lag 3 | -0.050* | -0.055* | -0.051** |
| | (0.027) | (0.030) | (0.024) |
| NEER Lag 4 | 0.003 | 0.018 | -0.004 |
| | (0.012) | (0.012) | (0.011) |
| Cum. Sum of NEER Coefficients | -0.303 | -0.295 | -0.300 |
| F-Statistic NEER Lags | 50.360 | 44.158 | 54.238 |
| Output Gap (+4 Lags) | Yes | Yes | Yes |
| Trade-Weighted PPI YoY Change (+4 Lags) | Yes | Yes | Yes |
| Country Fixed Effects | Yes | Yes | Yes |
| Standard Errors | Clustered | Clustered | Clustered |
| Observations | 910 | 910 | 910 |
| R-Squared | 0.587 | 0.585 | 0.579 |
| | Standard Errors in Parentheses | | |
| | ***p<0.01, **p<0.05, *p<0.1 | | |

**Note:** This table shows the result of estimating equation (6) with the NEER_XI from the ECB, BIS and IMF as exchange rate variable, respectively. The dependent variable is the import deflator.

and Ireland, up to 25 percent for the Netherlands.

Second, the total trade shares depicted in Figure 5 exhibit temporal variations. Not only do they reveal a certain trend, but also display fluctuations over the years. These variations imply that infrequent updates of trade weights may not adequately capture the dynamics of trade relationships.

Third, export and import relationships for euro area countries with a specific partner country can vary remarkably. In other words, euro NEER_XI and euro NEER_XI_C movements may differ from euro NEER_I and euro NEER_I_C movements, respectively. This is exemplified in Figure 6, which shows the difference between export trade shares and import trade shares of the United States and China for the sample countries. The calculation of export and import trade shares closely resembles the method described in equation (8), with the distinction that trade is confined either to exports or imports in the numerator and denominator, respectively. For the majority of the sample countries, the United States plays a more significant role as an export destination than as an import origin. For example, Germany's export share to the United States exceeds its import share by more than 5 percentage points in recent years. On the contrary, China serves as a more significant import origin than export destination for all of the euro area countries considered, except

Table 4: Estimation results of ERPT to aggregate consumer prices using publicly available euro NEER_XI

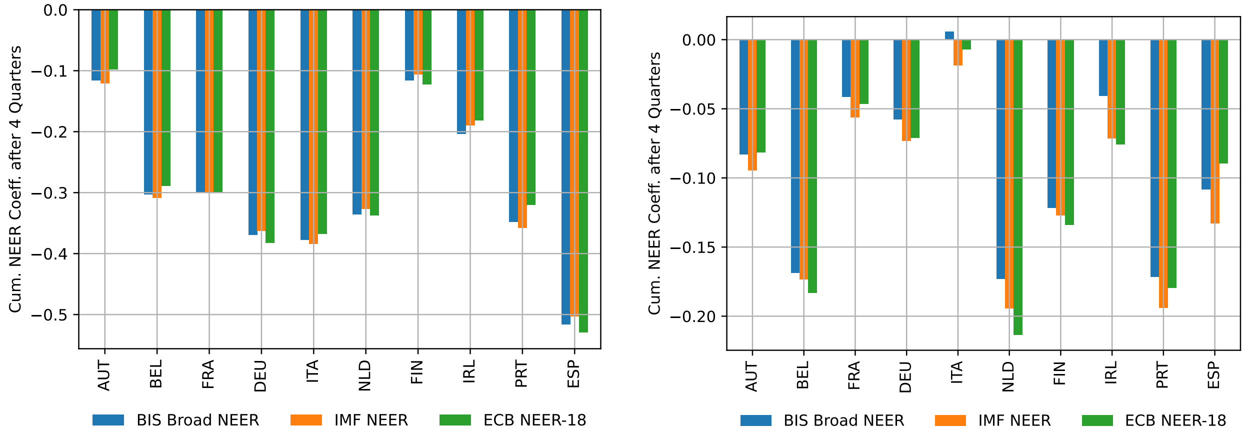
| | Dependent Variable: HICP Goods | | |
|---|---|---|---|
| | BIS Broad NEER | ECB NEER-18 | IMF NEER |
| Constant | 0.001*** | 0.000* | 0.001*** |
| | (0.000) | (0.000) | (0.000) |
| NEER | -0.024*** | -0.012 | -0.034*** |
| | (0.007) | (0.008) | (0.007) |
| NEER Lag 1 | 0.016*** | 0.003 | 0.018*** |
| | (0.003) | (0.003) | (0.003) |
| NEER Lag 2 | -0.033*** | -0.030*** | -0.038*** |
| | (0.006) | (0.009) | (0.005) |
| NEER Lag 3 | -0.005 | -0.028*** | 0.001 |
| | (0.008) | (0.008) | (0.008) |
| NEER Lag 4 | -0.054*** | -0.045*** | -0.064*** |
| | (0.009) | (0.009) | (0.009) |
| Cum. Sum of NEER Coefficients | -0.100 | -0.113 | -0.117 |
| F-Statistic NEER Lags | 77.919 | 40.656 | 102.365 |
| Output Gap (+4 Lags) | Yes | Yes | Yes |
| Trade-Weighted PPI YoY Change (+4 Lags) | Yes | Yes | Yes |
| Country Fixed Effects | Yes | Yes | Yes |
| Standard Errors | Clustered | Clustered | Clustered |
| Observations | 910 | 910 | 910 |
| R-Squared | 0.249 | 0.249 | 0.243 |
| | Standard Errors in Parentheses | | |
| | ***p<0.01, **p<0.05, *p<0.1 | | |

**Note:** This table shows the result of estimating equation (6) with the euro NEER_XI from the ECB, BIS and IMF as exchange rate variable, respectively. The dependent variable is the HICP goods.

for Finland. Referring again to Germany, the export share to China is about 6 percentage points lower than the import share in 2022. Consequently, the exchange rate of the euro to the US dollar would receive a larger weight in the euro NEER (be it country-specific or not) if the trade base was export and import trade flows, and a smaller weight if the trade base was solely import trade flows, with the inverse holding true for the Chinese yuan.

Fourth, the euro's bilateral nominal exchange rates do not consistently follow the same trend, as evidenced by the correlation matrix of the euro's quarter-on-quarter growth rates in bilateral nominal exchange rates in Table 5. With a mean correlation of 0.186 and a median of 0.088, the data suggests only a weak positive relationship, i.e., the euro's bilateral nominal exchange rates do not always follow the same trend. This indicates variation in the euro's movements against different trading partners' currencies, suggesting that the choice of the trade base in calculating euro NEERs could significantly influence aggregate ERPT estimates. The table also reveals, however, that some significant currency pairs, such as EUR/USD and EUR/CNY, tend to move more closely together. This concurrent movement might imply that the selection of the trade base may not necessarily have a substantial impact on the ERPT estimates for certain euro area countries.

Figure 4: One year ERPT to aggregate prices for euro area countries using publicly available euro NEER_XI




(a) Import deflator

(b) HICP

**Note:** This figure depicts the cumulative sum of the coefficients $\beta_k$ after four quarters from equation (6) for each of the euro area countries in the sample. Note that all NEERs are defined in such a way that an increase represents an appreciation of the domestic currency.

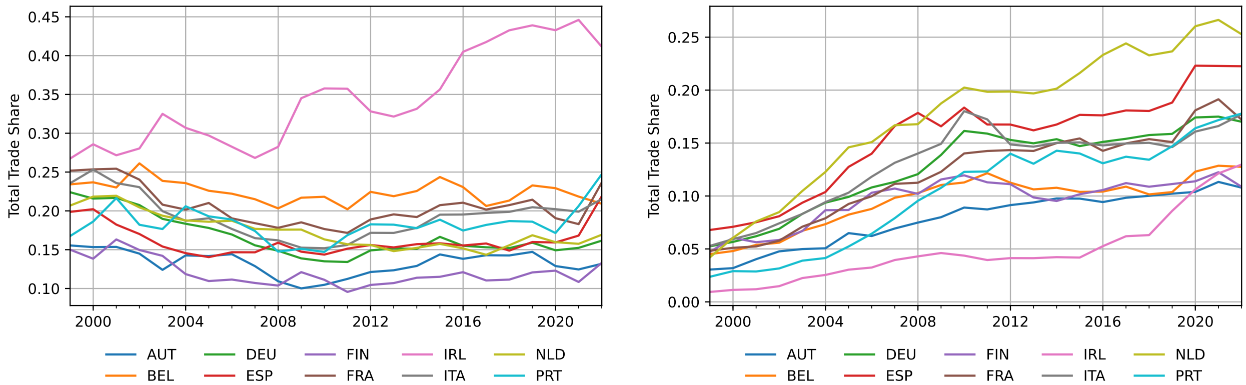
These findings imply that the choice of the euro NEER could significantly affect ERPT estimates. More specifically, using euro NEER_I_C, with weights that are frequently updated, may provide different ERPT estimates than relying on euro NEER_XI based on weights that are updated less frequently (approximately every three years). This is highly relevant since, as the theoretical perspective in Section 2.3. suggests, euro NEER_I_C are expected to provide more accurate results than euro NEER_XI, confirming the 'thought' of Colavecchio & Rubene (2020, p.9). However, empirical research has predominantly applied the latter measure (see Section 2.2.).

Addressing the first factor – i.e. that aggregated euro area trade shares may mask the specific importance of particular trading partners for individual countries within the euro area – could involve using equation (6) with euro NEER_XI_C provided by the BIS and IMF. This implies that $\Delta NEER_{t-k}$ and $Foreign\_PPI\_YoY_{t-k}$ become country-specific via the subscript $j$. Additionally, the set of partner countries, $N$, is expanded to include the 19 euro area partner countries. The latest trade weights underlying these officially published euro NEER_XI_C are shown in Tables 12 and 13 in Appendix C.[7] It is crucial to note that, while these euro NEERs are country-specific, they include intra-euro area trade. This component, transacted at a fixed EUR/EUR exchange rate, significantly influences the calculation of euro NEERs due to the substantial volume of intra-euro area trade.[8] Given the large share of intra-euro area trade in total trade, the movements in these euro NEER_XI_C tend to be restricted. This is evidenced by comparing the standard

[7]Acknowledgements to the IMF for providing the requested trade weights.

[8]To highlight the relevance: When examining the 2017-2022 period, the average trade weight of the United States (China) stands at 9.3 percent (10 percent) across the sample countries according to the trade weights underlying the BIS euro NEER_XI_C. However, this percentage rises to 18 percent (24 percent) when considering the 2017-2022 trade weights underlying the BIS euro NEER_XI. Similarly, with respect to the IMF's 2016-2022 trade weights underlying the euro NEER_XI_C, the United States (China) possesses an average adjusted trade weight of 11 percent (11 percent) across the sample countries. Yet, this values jumps to 24 percent (24 percent) within the IMF's 2016-2022 trade weights underlying the euro NEER_XI.

Figure 5: Dynamics of total trade shares for euro area countries




(a) United States

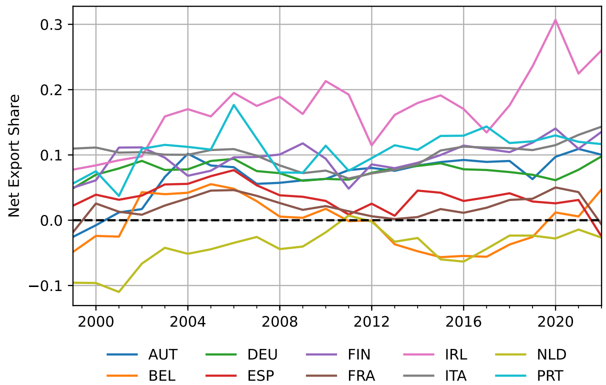
(b) China

**Note:** This figure depicts the total trade shares of the United States and China over time for the sample countries. The total trade shares are computed according to equation (8). The underlying data is taken from IMF DOTS.

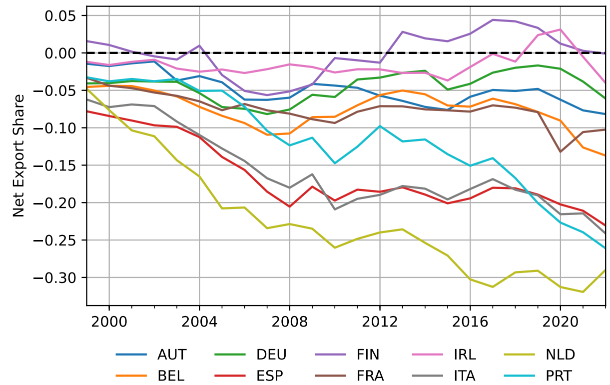
deviations of the BIS‘s euro NEER_XI (0.022) and BIS's euro NEER_XI_C (0.011), as well as the standard deviations of the IMF's euro NEER_XI (0.023) and IMF's euro NEER_XI_C (0.012). As a result, there is a notable divergence between aggregate ERPT estimates derived from country-specific and non country-specific euro NEERs. This can be observed in Figure 7, which depicts ERPT to both aggregate import and consumer prices across varying time horizons within a year utilizing the BIS's and IMF's euro NEER_XI_C. The underlying regression results can be found in Tables 14 and 15 in Appendix C. To illustrate, the size of ERPT to aggregate import prices and consumer prices after one year stands at about 43 to 45 percent and 16 to 17 percent, respectively, when calculations are based on the euro NEER_XI_C (including intra-euro area trade). However, these values change to about 30 percent and 10 to 12 percent, respectively, when utilizing the corresponding euro NEER_XI (see Figure 3). As Colavecchio & Rubene (2020) suggest, given that euro NEERs that include intra-euro area trade encompasses a considerable proportion that remains constant, the most relevant euro NEER from a policymaker's perspective is the one based solely on trade flows with countries outside the euro area. Therefore, although it is beneficial to take into account the heterogeneity in trade patterns across individual euro area countries when computing euro NEERs, incorporating intra-euro area trade might not be the most favorable approach.

The forthcoming section aims to address the four key factors outlined above that could potentially influence ERPT estimates, specifically in relation to the computation of euro NEERs. These are: The choice between using total trade flows or import trade flows as trade base, the frequency of updating the trade weights, the decision to use euro area-wide euro NEERs as opposed to country-specific euro NEERs, and the inclusion or exclusion of intra-euro area trade. By comparing different euro NEERs, the objective is to identify which aspects may notably influence aggregate ERPT estimates, while also highlighting those that seem to exert less effect.

Figure 6: Dynamics of net export trade shares for euro area countries




(a) United States




(b) China

**Note:** This figure depicts the difference between the export trade share and the import trade share of the United States and China for the sample countries. The calculation of export and import trade shares closely resembles the method described in equation (8), with the distinction that trade is confined either to exports or imports in the numerator and denominator, respectively. The underlying data is taken from IMF DOTS.

## 2.5. Computing euro NEERs for the assessment of ERPT to aggregate prices in the euro area

To highlight the reliability of ERPT estimates based on IMF DOTS data, the ECB NEER-18 is reproduced employing the ECB's methodology (see Schmitz et al., 2012 and Fidora & Schmitz, 2020), but utilizing IMF DOTS data. The trade weights are computed as a weighted average of the export and import weights, with the export weights incorporating 'third-market effects'. In order to replicate the ECB's euro NEER_XI, data on export and import trade by partner country and nominal bilateral exchange rates (NER) are required.

Bilateral US dollar NERs are taken from the IMF International Financial Statistics (IFS) database, which offers monthly data on economic indicators for 194 countries and areas worldwide. The NER of country $j$ against partner country $i$ at time $t$ is then computed as:

$$NER_{j/i,t} = NER_{j/US,t} \times \frac{1}{NER_{i/US,t}} \tag{9}$$

where $NER_{j/i,t}$ denotes the NER between country $j$ and partner country $i$ at time $t$ in quantity notation, i.e. partner country $i$ currency units per one currency unit of country $j$. $NER_{j/US,t}$ gives the NER between country $j$ and the United States at time $t$ in quantity notation, i.e. the amount of US dollars per one currency unit of country $j$. Finally, $NER_{i/US,t}$ denotes the NER between country $i$ and the United States at time $t$ in quantity notation, i.e. the amount of US dollars per one currency unit of country $i$.

This approach generates a NER matrix with over 150 columns and rows, providing monthly data from 1999 to 2022. The bilateral nominal US dollar exchange rates are utilized to compute the NER matrix

Table 5: Correlation matrix of quarter-on-quarter growth rates in nominal bilateral euro exchange rates

| | EUR/AUD | EUR/BGN | EUR/CAD | EUR/HKD | EUR/CNY | EUR/CZK | EUR/DKK | EUR/HUF | EUR/JPY | EUR/KRW | EUR/NOK | EUR/PLN | EUR/RON | EUR/SGD | EUR/SEK | EUR/CHF | EUR/GBP | EUR/USD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EUR/AUD | 1 | 0.08 | 0.59 | 0.04 | 0.06 | 0.18 | 0.04 | 0.31 | -0.07 | 0.52 | 0.60 | 0.34 | 0.15 | 0.25 | 0.54 | 0.00 | 0.32 | 0.05 |
| EUR/BGN | 0.08 | 1 | 0.02 | -0.16 | -0.15 | -0.06 | 0.08 | -0.03 | -0.14 | -0.06 | 0.00 | -0.07 | -0.04 | -0.11 | -0.01 | -0.17 | -0.11 | -0.15 |
| EUR/CAD | 0.59 | 0.02 | 1 | 0.57 | 0.55 | 0.09 | -0.01 | 0.08 | 0.27 | 0.60 | 0.46 | 0.27 | 0.10 | 0.65 | 0.33 | 0.18 | 0.40 | 0.57 |
| EUR/HKD | 0.04 | -0.16 | 0.57 | 1 | 0.91 | -0.23 | -0.08 | -0.25 | 0.57 | 0.46 | -0.02 | -0.05 | 0.03 | 0.86 | -0.13 | 0.47 | 0.37 | 1.00 |
| EUR/CNY | 0.06 | -0.15 | 0.55 | 0.91 | 1 | -0.14 | -0.07 | -0.17 | 0.55 | 0.45 | 0.04 | 0.00 | 0.03 | 0.85 | -0.08 | 0.43 | 0.42 | 0.91 |
| EUR/CZK | 0.18 | -0.06 | 0.09 | -0.23 | -0.14 | 1 | -0.05 | 0.58 | -0.17 | 0.07 | 0.36 | 0.63 | 0.16 | -0.01 | 0.36 | -0.03 | 0.19 | -0.22 |
| EUR/DKK | 0.04 | 0.08 | -0.01 | -0.08 | -0.07 | -0.05 | 1 | 0.07 | -0.09 | 0.00 | 0.04 | -0.04 | -0.03 | -0.04 | 0.05 | 0.04 | -0.07 | -0.07 |
| EUR/HUF | 0.31 | -0.03 | 0.08 | -0.25 | -0.17 | 0.58 | 0.07 | 1 | -0.28 | 0.18 | 0.34 | 0.67 | 0.27 | -0.06 | 0.38 | -0.11 | 0.26 | -0.24 |
| EUR/JPY | -0.07 | -0.14 | 0.27 | 0.57 | 0.55 | -0.17 | -0.09 | -0.28 | 1 | 0.24 | -0.07 | -0.28 | -0.16 | 0.61 | -0.11 | 0.46 | 0.09 | 0.56 |
| EUR/KRW | 0.52 | -0.06 | 0.60 | 0.46 | 0.45 | 0.07 | 0.00 | 0.18 | 0.24 | 1 | 0.41 | 0.27 | 0.31 | 0.61 | 0.32 | 0.22 | 0.58 | 0.47 |
| EUR/NOK | 0.60 | 0.00 | 0.46 | -0.02 | 0.04 | 0.36 | 0.04 | 0.34 | -0.07 | 0.41 | 1 | 0.31 | 0.05 | 0.20 | 0.41 | 0.06 | 0.23 | -0.01 |
| EUR/PLN | 0.34 | -0.07 | 0.27 | -0.05 | 0.00 | 0.63 | -0.04 | 0.67 | -0.28 | 0.27 | 0.31 | 1 | 0.37 | 0.09 | 0.43 | -0.08 | 0.31 | -0.05 |
| EUR/RON | 0.15 | -0.04 | 0.10 | 0.03 | 0.03 | 0.16 | -0.03 | 0.27 | -0.16 | 0.31 | 0.05 | 0.37 | 1 | 0.09 | 0.25 | -0.07 | 0.20 | 0.04 |
| EUR/SGD | 0.25 | -0.11 | 0.65 | 0.86 | 0.85 | -0.01 | -0.04 | -0.06 | 0.61 | 0.61 | 0.20 | 0.09 | 0.09 | 1 | 0.06 | 0.52 | 0.43 | 0.86 |
| EUR/SEK | 0.54 | -0.01 | 0.33 | -0.13 | -0.08 | 0.36 | 0.05 | 0.38 | -0.11 | 0.32 | 0.41 | 0.43 | 0.25 | 0.06 | 1 | -0.09 | 0.34 | -0.12 |
| EUR/CHF | 0.00 | -0.17 | 0.18 | 0.47 | 0.43 | -0.03 | 0.04 | -0.11 | 0.46 | 0.22 | 0.06 | -0.08 | -0.07 | 0.52 | -0.09 | 1 | 0.11 | 0.47 |
| EUR/GBP | 0.32 | -0.11 | 0.40 | 0.37 | 0.42 | 0.19 | -0.07 | 0.26 | 0.09 | 0.58 | 0.23 | 0.31 | 0.20 | 0.43 | 0.34 | 0.11 | 1 | 0.38 |
| EUR/USD | 0.05 | -0.15 | 0.57 | 1.00 | 0.91 | -0.22 | -0.07 | -0.24 | 0.56 | 0.47 | -0.01 | -0.05 | 0.04 | 0.86 | -0.12 | 0.47 | 0.38 | 1 |

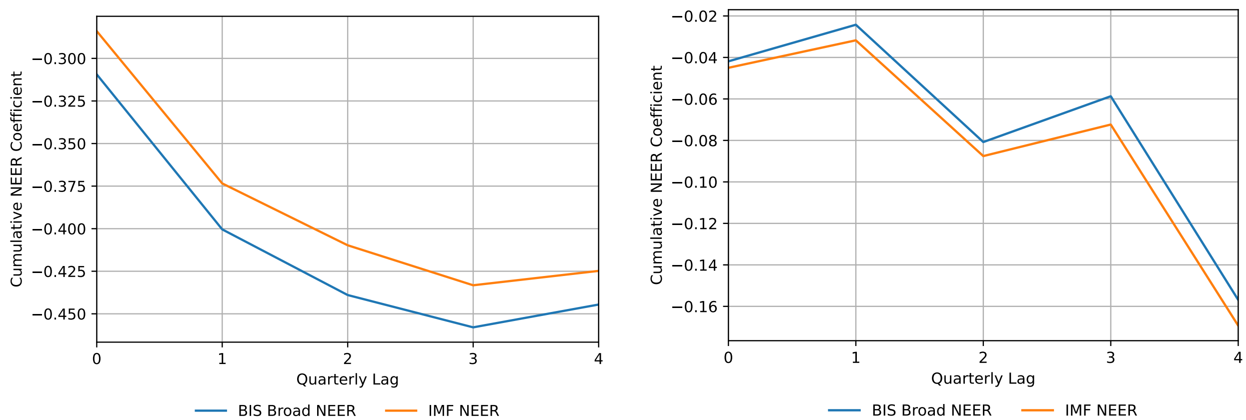
**Note:** This table presents the correlation matrix of quarter-on-quarter growth rates in the bilateral nominal exchange rates between the euro and the currencies of the ECB's set of partner countries for its euro NEER-18 calculation. Each cell reflects the correlation coefficient between the euro's growth rate in exchange rate against a pair of foreign currencies over 1999Q2-2022Q4. A positive value indicates that the growth rates in exchange rates move in the same direction and negative value indicates that they move in opposite directions. The color gradient from dark green to dark red represents the highest to lowest values, respectively.

because of the absence of NERs for less common currency pairs in conventional macroeconomic datasets.[9] The computed NERs prove to be highly precise, as demonstrated in Figure 8, in which the self-constructed nominal EUR/PLN and EUR/TRY series are compared with the one extracted from ECB SDW. Note that quantity notation is used to align the NER notation to the NEER notation, which is the quantity notation by default.

The trade data is taken from the IMF DOTS database, where it is characterized as merchandise exports and imports by trade partner country. Countries within the euro area are excluded from the set of trade partners. Additional details on the data sources and definitions of variables can be found in Appendix B. Upon integrating the NER data and trade data, a dataset is created that features exports, imports and NERs for the ten largest euro area countries and the euro area as a whole, against each of the 18 partner countries as defined in the ECB NEER-18. This collective data is then exploited to compute the euro NEER_XI – in

[9] While this work-around is not strictly necessary for this project as the nominal bilateral euro exchange rates against the currencies of the 18 partner countries are readily available in the ECB Statistical Data Warehouse (SDW), the NER matrix methodology was maintained for two reasons: i) the derived exchange rate series perfectly align with the provided data, and ii) the NER matrix allows to conduct robustness checks using a broader group of countries.

Figure 7: Dynamics of ERPT to aggregate prices using publicly available NEER_XI_C (incorporating intra-euro area trade)




(a) Import deflator

(b) HICP

**Note:** This figure depicts the cumulative sum of the $\beta_k$ coefficients from equation (6) with country-specific $\Delta NEER_{j,t-k}$ and $Foreign\_PPI\_YoY_{j,t-k}$. Additionally, the set of partner countries, $N$, is expanded to include the 19 euro area partner countries. Note that all NEERs are defined in such a way that an increase represents an appreciation of the domestic currency. By using four lags, the model shows the relationship between NEER quarter-on-quarter growth rates and aggregate price quarter-on-quarter growth rates at different horizons within a year. At the annual horizon, this empirical evidence suggests that a 1 percent nominal effective depreciation in the euro raises aggregate import (consumer) prices by, on average, 0.43-0.45 (0.16-0.17) percent.

line with the ECB's method – as follows:

$$NEER_t = \prod_{i=1}^{N} (E_{i,t})^{w_i} \tag{10}$$

This equation implies that the euro NEER_XI is calculated as a geometric weighted average of bilateral exchange rates. In this equation, $NEER_t$ represents the euro NEER_XI at time $t$. $E_{i,t}$ is the bilateral nominal euro exchange rate relative to the currency of trading partner $i$ at time $t$ in quantity notation, i.e. the amount of foreign currency per one euro, and $w_i$ is the trade weight assigned to the currency of trading partner $i$ based on IMF DOTS data. These weights are obtained as the weighted average of the export and import weights:

$$w_i = \frac{M}{X+M} \times w_i^m + \frac{X}{X+M} \times w_j^x, \tag{11}$$

Here, $w_i^m$ and $w_i^x$ are partner country $i$'s import and export weights, and $M$ and $X$ are total imports and total exports by the euro area, respectively.

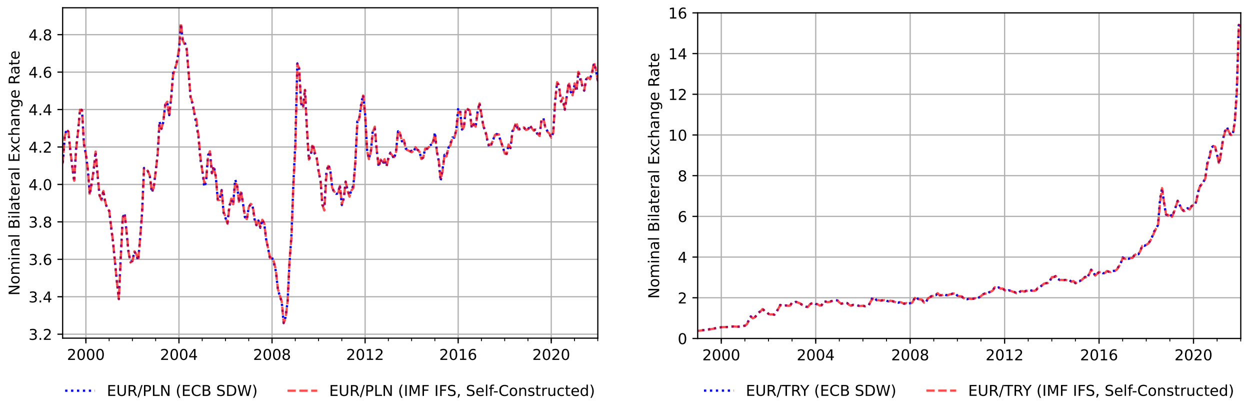
The import weight of partner country $i$ is its simple share of total imports from the $N = 18$ partner countries:

$$w_i^m = \frac{M_i}{\sum_{i=1}^{N=18} M_i} \tag{12}$$

where $M_i$ gives the import value into the euro area from country $i$ during the reference period.

The export weights take 'third market effects' into account, i.e. the competition faced by euro area

Figure 8: Comparison of officially published and self-constructed nominal bilateral exchange rates




(a) EUR/PLN (b) EUR/TRY

**Note:** This figure depicts two series of the EUR/PLN and EUR/TRY nominal exchange rate. The self-constructed series is computed according to equation (9).

exporters from i) domestic producers, and ii) exporters of the countries included in the group of trading partners, in the economies of the other trading partners. In order to compute these 'double export weights', first the share of each foreign country in total euro area exports is calculated:

$$x_r = \frac{X_r}{\sum_{r=1}^{W} X_r} \tag{13}$$

where $X_r$ denotes the export value in the reference period from the euro area to country $r$. Note that the export trading partners are not restricted to $N = 18$ but include all potential export markets $W$.

The next step involves adjusting euro area export shares to account for third-market effects, as depicted by the following equation:

$$w_i^x = \sum_{r=1}^{W} (s_{i,r} \times x_r) \tag{14}$$

In this equation, $i$ refers to the ECB NEER-18 group of trading partners. The factor $s_{i,r}$ designates the proportion of country $i$'s output supplied to market $r$, computed as:

$$s_{i,r} = \frac{S_{i,r}}{\sum_{i=1}^{N} S_{i,r}} \tag{15}$$

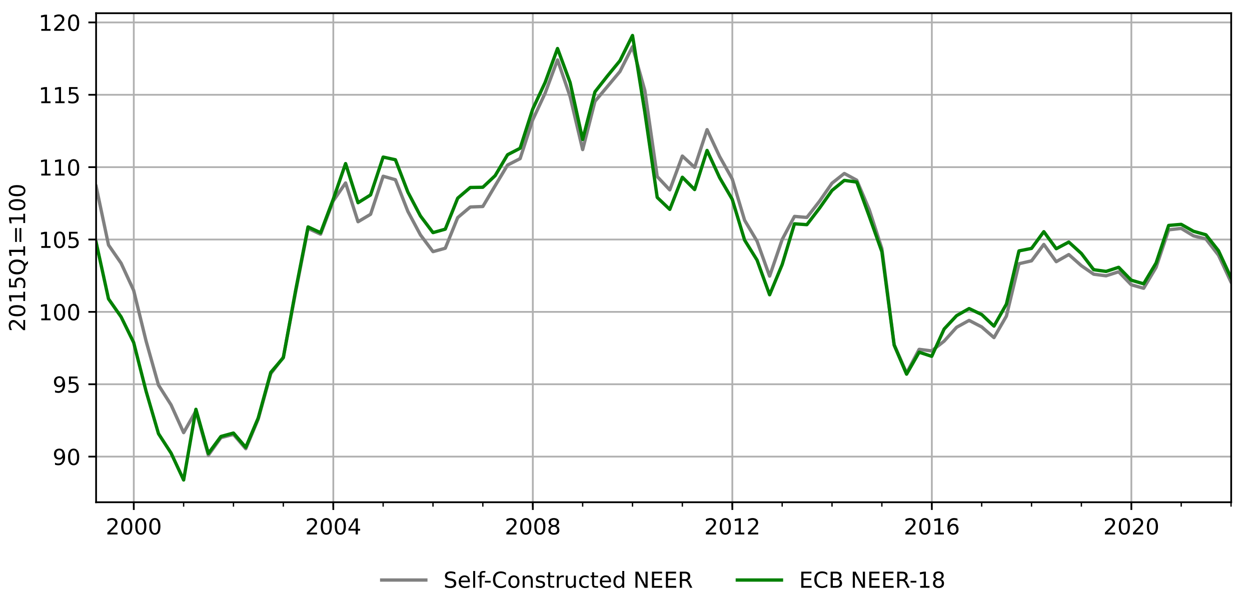
Here, $S_{i,r}$ represents the value of exports from country $i$ to country $r$ (for all $i \neq r$, and $i = 1, 2, \ldots, N$, and $r = 1, 2, ..., W$). Simultaneously, $S_{i,i}$ denotes the value of goods produced in country $i$ that are marketed domestically (for all $i = 1, 2, \ldots, N$). The latter value is derived from domestic value added in final demand data series sourced from the OECD Trade in Value Added (TiVA) database.

A more comprehensive breakdown of the computation of export weights is available in Schmitz et al. (2012). Tables 16 to 22 in Appendix C provide an overview of all elements involved in the calculation of the trade weights for all periods and offer an example of how the overall trade weights are computed in practice.

Trade weights underlying the euro NEER_XI, as computed by the ECB, are time-varying as they are calculated over distinct three-year periods (e.g., 1998-2000, 2001-03, 2004-06, and so on). In this study, the first period is shortened to 1999-2000 due to the constructed database commencing in 1999. Adhering to the ECB's approach, euro NEER_XI are computed on a monthly basis for these periods, and are subsequently chain-linked at the conclusion of each period.

Overall, the computation methodology aligns with the ECB's, albeit utilizing a distinct underlying database (IMF DOTS for import and export values, and OECD TiVA for the share of each country's total supply resulting from its own domestic production). A comparison of this self-computed euro NEER_XI with the official ECB's euro NEER_XI is presented in Figure 9. The close alignment of the curves affirms the high degree of comparability between IMF DOTS trade data and the trade data employed by the ECB for its NEER-18 computation. Moreover, ERPT estimates using the self-computed euro NEER_XI demonstrate a very strong resemblance to those presented in Figure 3.

Figure 9: Comparison of the ECB's euro NEER_XI and the self-computed counterpart




**Note:** This figure displays both the ECB NEER-18 and the self-computed euro NEER_XI. The latter follows the ECB's methodology as detailed in Schmitz et al. (2012) and Fidora & Schmitz (2020), but utilizes trade data sourced from the IMF DOTS. The procedure for this computation is outlined from equation (10) through equation (15).

Addressing the conjecture presented in Section 2.3., which postulates that euro NEER_I may be more applicable for assessing aggregate ERPT estimates than euro NEER_XI, an alternative euro NEER is computed. In this version, the trade weights are derived solely from import data. In light of this, the euro NEER_I is computed as follows:

$$NEER_t = \prod_{i=1}^{N} (E_{i,t})^{w_i} \tag{16}$$

Here, $w_i$ is the trade weight assigned to the currency of trading partner $i$, calculated solely based on import data:

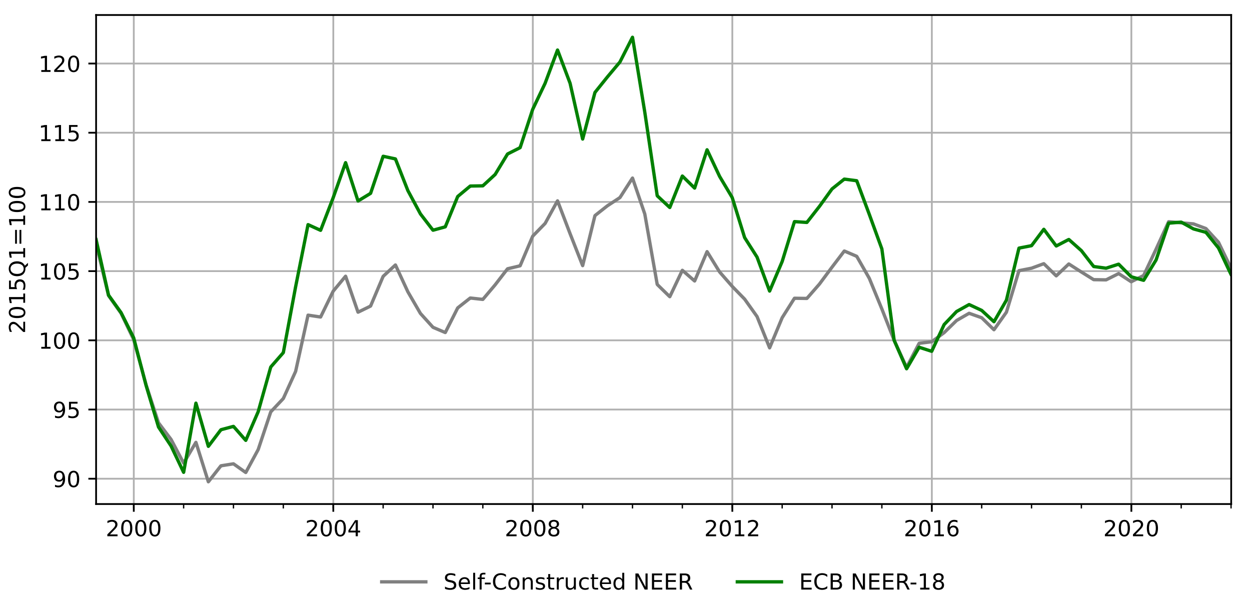
$$w_i = \frac{M_i}{\sum_{i=1}^{N} M_i} \tag{17}$$

In this equation, $M_i$ represents the import value from country $i$ into the euro area over the defined reference period. The trade weights, therefore, are obtained as the proportions of each partner country $i$'s imports to the total imports from the $N = 18$ partner countries. In this methodology, export values are not considered.

Continuing the ECB's approach outlined before, trade weights are calculated over non-overlapping three-year periods, such as 1998-2000, 2001-03, 2004-2006, etc. Following this, euro NEER_I is computed at a monthly frequency for each of these periods and then chain-linked at the conclusion of each respective period.

Figure 10 provides a comparative view of the self-computed euro NEER_I and the official ECB's euro NEER_XI. The divergence of the curves indicates a potentially significant impact of the chosen euro NEER – whether it is computed solely based on import trade flows or on total trade flows including third market effects – on ERPT estimates.

Figure 10: Comparison of the ECB's euro NEER_XI and the self-computed euro NEER_I

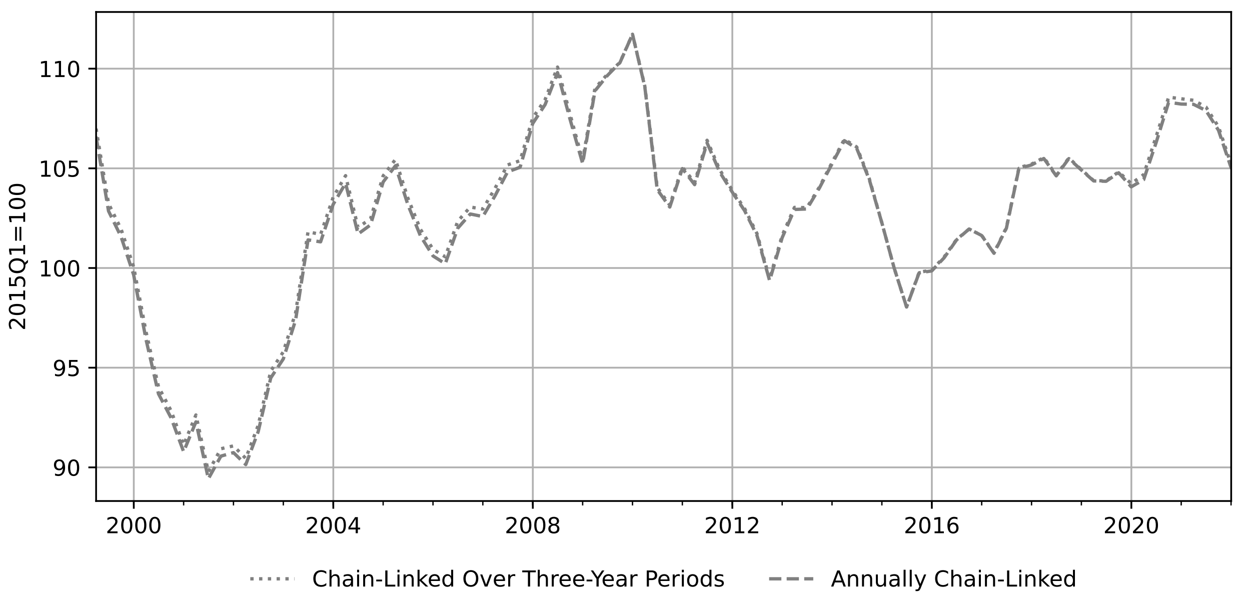



**Note:** This figure displays both the ECB NEER-18 and the self-computed euro NEER_I. Note that for the latter, trade weights are calculated solely based on import trade flows as outlined in equation (17).

In order to investigate the influence of the updating frequency of trade weights, the computation of the euro NEER_I is carried out again, but with trade weights updated more frequently. Rather than every three years, trade weights are now computed for each non-overlapping one-year period from 1999 to 2022. As before, monthly euro NEER_I are computed for each period (now the years) and subsequently chain-linked at the end of each period. This approach adheres to the ECB's recommendation that more frequent updates to trade weights would be desirable (Schmitz et al., 2012, p.18). However, they suggest that calculating third market effects would be hindered by data availability limitations. Since the trade weights are based on import trade flows alone and are therefore not affected by third market effects, combined with the fact that IMF DOTS provides trade data on a monthly basis, more frequent updating of trade weights is a straightforward approach in this context.

Figure 11 juxtaposes the self-computed euro NEER_I, with weights updated every three years, with the same euro NEER_I but weights updated annually. The two series largely coincide, corroborating the findings of Rueffer & Mauro & Bunda (2008) that more frequent updates to trade weights have a limited influence on the computed euro NEER.

Figure 11: Comparison of self-computed euro NEER_I with different chain-linking




**Note:** This figure shows the self-computed euro NEER_I, with weights updated every three years, with the same euro NEER_I but weights updated annually.

To investigate the potential impacts of aggregating trade weights across all euro area countries, euro NEER_I_C are calculated based on the countries' specific import weights against the $N = 18$ trading partners. The euro NEER_I_C versions are computed as follows:

$$NEER_{j,t} = \prod_{i=1}^{N} (E_{j/i,t})^{w_{ji}} \tag{18}$$

In this equation, $NEER_{j,t}$ represents the euro NEER_I_C for euro area country $j$ at time $t$. $E_{j/i,t}$ is the bilateral nominal euro exchange rate relative to the currency of trading partner $i$ at time $t$ in quantity notation, i.e. the amount of foreign currency per one euro, and $w_{ji}$ designates the trade weight that country $j$ assigns to the currency of trading partner $i$, indicative of country $j$'s import proportion from country $i$.

More specifically:

$$w_{ji} = \frac{M_{ji}}{\sum_{i=1}^{N} M_{ji}} \tag{19}$$

Here, $M_{ji}$ indicates the import value of euro area country $j$ from country $i$ during the reference period. Consequently, the trade weights are defined by country $j$'s import shares of trading partner country $i$, represented as a simple fraction of total imports from the $N = 18$ partner countries. These weights thus express the relative significance of each trading partner based on its contribution to country $j$'s imports. It also suggests that the larger the proportion of country $i$ in country $j$'s imports, the more substantial the weight assigned to its bilateral nominal euro exchange rate. To keep the computations consistent to the previously computed euro NEER_I, trade weights are calculated on an annual level from 1999-2022. Following this, euro NEER_I_C are determined on a monthly basis for these years and then chained at the close of each year.

Figure 12 juxtaposes the self-computed euro NEER_I_C with the self-computed euro NEER_I. It becomes apparent that there is considerable variation in the euro NEER across different countries. Moreover, Table 6 illustrates the correlation between the quarter-on-quarter growth rates of the self-computed euro NEER_I_C and the ECB's euro NEER_XI. As displayed in the final row and column, the mean correlation coefficient between the euro NEER_I_C and the ECB NEER-18 is 0.89. This is substantially lower than the correlation observed between the quarter-on-quarter growth rates of the BIS's and IMF's euro NEER_XI with the ECB NEER-18, which averaged 0.98, as shown in Table 2. Given that quarter-on-quarter growth rates are incorporated into the distributed lag regression, it signifies that the calculated ERPT might vary based on the chosen euro NEER.

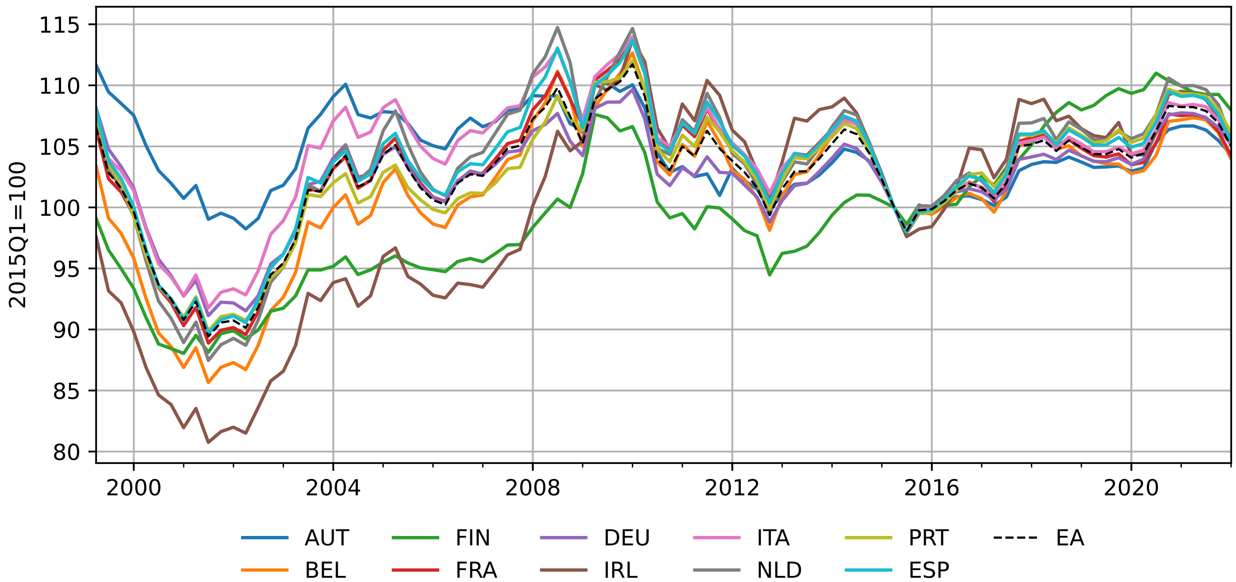
Table 6: Correlation matrix of euro NEER_I_C and ECB's NEER_XI quarter-on-quarter growth rates

| | AUT | BEL | DEU | ESP | FIN | FRA | IRL | ITA | NLD | PRT | ECB NEER-18 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUT | 1 | 0.84 | 0.95 | 0.85 | 0.77 | 0.88 | 0.78 | 0.89 | 0.81 | 0.87 | 0.83 |
| BEL | 0.84 | 1 | 0.95 | 0.99 | 0.73 | 0.99 | 0.92 | 0.98 | 0.99 | 0.97 | 0.93 |
| DEU | 0.95 | 0.95 | 1 | 0.96 | 0.81 | 0.97 | 0.89 | 0.98 | 0.94 | 0.97 | 0.92 |
| ESP | 0.85 | 0.99 | 0.96 | 1 | 0.74 | 0.99 | 0.93 | 0.99 | 0.99 | 0.98 | 0.94 |
| FIN | 0.77 | 0.73 | 0.81 | 0.74 | 1 | 0.76 | 0.75 | 0.74 | 0.68 | 0.82 | 0.69 |
| FRA | 0.88 | 0.99 | 0.97 | 0.99 | 0.76 | 1 | 0.94 | 0.99 | 0.98 | 0.98 | 0.94 |
| IRL | 0.78 | 0.92 | 0.89 | 0.93 | 0.75 | 0.94 | 1 | 0.90 | 0.89 | 0.96 | 0.87 |
| ITA | 0.89 | 0.98 | 0.98 | 0.99 | 0.74 | 0.99 | 0.90 | 1 | 0.98 | 0.97 | 0.94 |
| NLD | 0.81 | 0.99 | 0.94 | 0.99 | 0.68 | 0.98 | 0.89 | 0.98 | 1 | 0.95 | 0.92 |
| PRT | 0.87 | 0.97 | 0.97 | 0.98 | 0.82 | 0.98 | 0.96 | 0.97 | 0.95 | 1 | 0.92 |
| ECB NEER-18 | 0.83 | 0.93 | 0.92 | 0.94 | 0.69 | 0.94 | 0.87 | 0.94 | 0.92 | 0.92 | 1 |

**Note:** This table presents the correlation matrix of quarter-on-quarter growth rates in the NEER_I_C and ECB NEER-18 over 1999Q2-2022Q4. The color gradient from dark green to dark red represents the highest to lowest values, respectively.

To summarize the findings thus far in this section: The euro NEER displays a significant divergence when it is computed based on export and import trade flows as compared to when it is derived solely from import trade flows. This variation could have implications for the estimation of aggregate ERPT. However, updating

Figure 12: Comparison of self-computed euro NEER_I and NEER_I_C




**Note:** This figure shows the self-computed euro NEER_I_C alongside the self-computed euro NEER_I. The former is spelled out in equations (18) and (19), while the latter is spelled out in equations (16) and (17). Both series are chain-linked on an annual basis.

the weights more frequently does not appear to be a significant factor. Most notably, there is substantial heterogeneity across the euro NEERs of the sample countries when country-specific trade weights are used. Therefore, the practice of aggregating over all euro area countries in the computation of the euro may lead to inaccurate aggregate ERPT estimates.

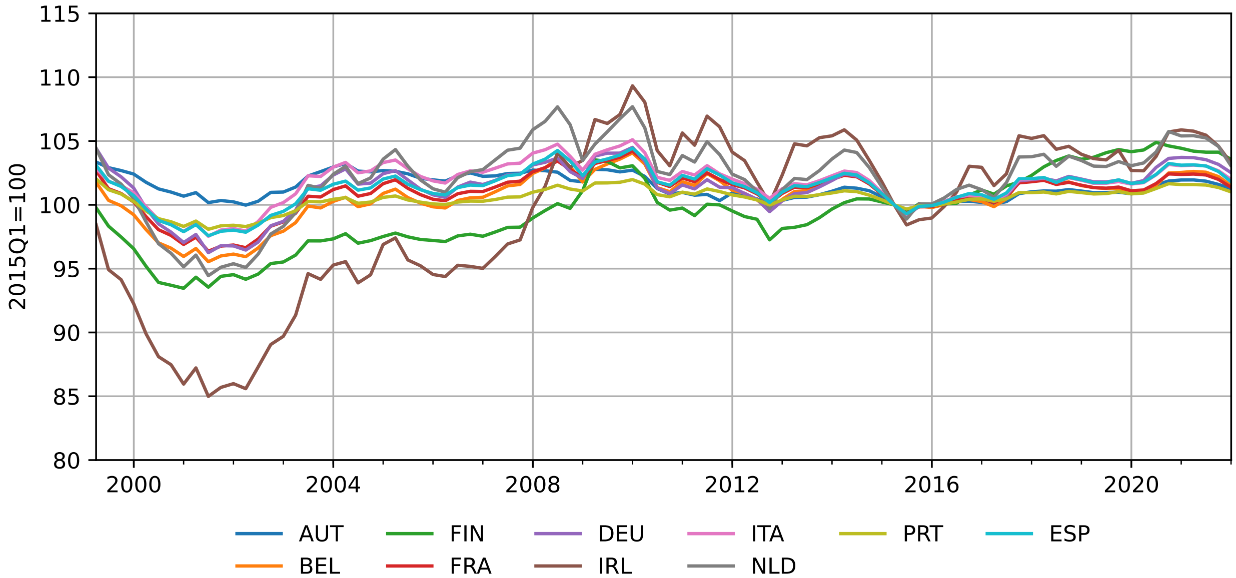
One unresolved question pertains to Figures 7 and 10, which demonstrate a difference in aggregate ERPT estimates depending on the inclusion or exclusion of intra-euro area trade. To what extent do country-specific euro NEERs deviate when considering intra-euro area trade? To investigate this aspect, euro NEER_I_C are recalculated as geometrically weighted averages of bilateral exchange rates, in accordance with equation (18). The computation of trade weights, however, is now defined as:

$$w_{ji} = \frac{M_{ji}}{\sum_{i=1}^{O} M_{ji}} \tag{20}$$

Here, as before, $M_{ji}$ represents the import value from country $i$ into euro area country $j$ during the reference period. The distinction lies in the inclusion of the other 19 euro area countries in the set of trading partners. In other words, trade weights are defined as the share of country $j$'s imports from partner country $i$ relative to total imports from the expanded set of $O = 18 + 19 = 37$ partner countries, which now comprises the initial $N = 18$ partners, plus the 19 euro area partner countries.

The resulting euro NEER_I_C (incorporating intra-euro area trade) are visualized in Figure 13, demonstrating divergent trends compared to Figure 12, where the set of trading partners is confined to countries outside the euro area. This indicates that including intra-euro area trade significantly influences the calculation and interpretation of euro NEERs, thereby implying that the overall trade relationships within the euro area do affect aggregate ERPT estimates.

Figure 13: Comparison of self-computed euro NEER_I_C (incorporating intra-euro area trade)




**Note:** This figure shows euro NEER_I_C with trade weights computed according to equation (20). Most notably, trade weights are defined as the share of country $j$'s imports from partner country $i$ relative to total imports from the expanded set of $O = 18 + 19 = 37$ partner countries, which now comprises the initial $N = 18$ partners, plus the 19 euro area partner countries. To facilitate a direct comparison, the y-scale is the same as in Figure 12.

## 2.6. New new reduced form empirical estimates of aggregate ERPT in the euro area

The goal of this section is to introduce and employ an iteration of equation (6) that incorporates NEER_I_C (excluding intra-euro area trade and with trade weights updated annually) as exchange rate variable. The revised equation is as follows:

$$\Delta Price_{j,t} = \alpha_0 + \sum_{k=0}^{4} \beta_k \Delta NEER_{j,t-j} + \sum_{k=0}^{4} \eta_j Output\_Gap_{j,t-k} + \sum_{k=0}^{4} \gamma_k Foreign\_PPI\_YoY_{j,t-k} + \mu_j + \epsilon_{j,t} \quad (21)$$

The innovative facet of this equation is the country-specific nature of both $\Delta NEER_{j,t-k}$ and $Foreign\_PPI\_YoY_{j,t-k}$. Also noteworthy is the fact that the country-specific euro NEERs are calculated based solely on import trade flows, excluding intra-euro area trade. From a computational viewpoint, these euro NEER_I_C are calculated using the same methodology as outlined in equations (18) to (19). The definitions and interpretations of the remaining variables remain consistent with those previously defined in the explanation for equation (6). This refined methodology for the computation of the euro NEER_I_C aims to provide more accurate empirical estimates of aggregate ERPT in the euro area.

The calculation of the country-specific quarterly import-weighted PPI growth rate, on a year-on-year basis, now takes the form:

$$Foreign\_PPI\_YoY_{j,t} = \sum_{i=1}^{N} PPI\_YoY_{ji,t} \times w_{ji,t} \tag{22}$$

Within this equation, $PPI\_YoY_{ji,t}$ denotes the year-on-year growth rate in the PPI for the $i$-th trading partner of euro area country $j$ at time $t$. The variable $w_{ji,t}$ corresponds to the weight assigned to that specific $i$-th trading partner of country $j$ at time $t$, which is based on import trade flows. The weights for all $N$ trading partners of country $j$ add up to one at any given time $t$. As before, the number of trading partners, represented by $N$, is capped at 18 due to the constrained availability of PPI data, thereby aligning with the ECB NEER-18 group of trading partners.

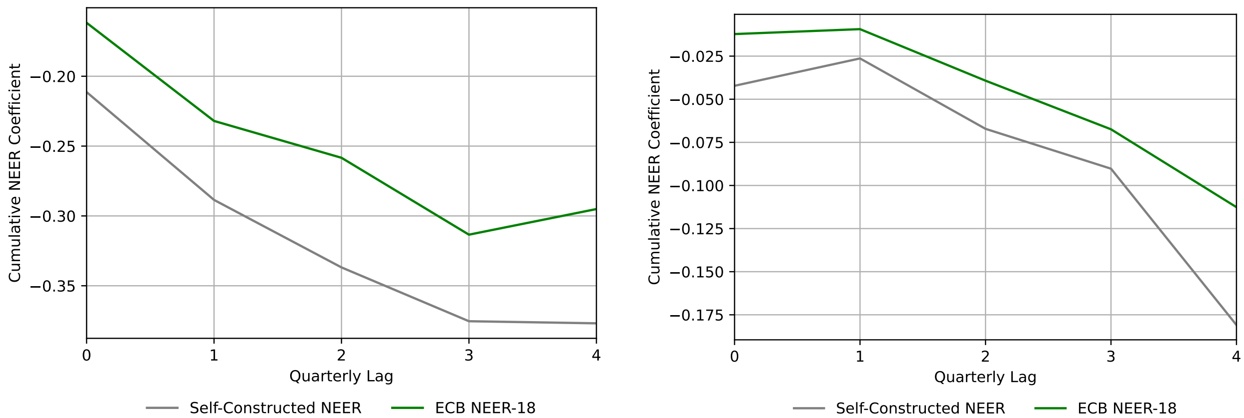
The resulting ERPT to aggregate prices is graphically presented as the grey lines in Figure 14. For a comprehensive view of the regression outcomes, see Table 7. Within a year, the magnitude of ERPT to aggregate import prices is 38 percent, whereas the magnitude of ERPT to aggregate consumer prices is just below half of that, at 18 percent. Figure 14 also presents the outcome of ERPT estimates to aggregate prices obtained by utilizing the ECB NEER-18 as the exchange rate variable, based on equation (6). These results are illustrated as the green lines. The ERPT estimates using self-constructed euro NEER_I_C significantly exceed those calculated using the euro NEER_XI from the ECB. More specifically, ERPT to aggregate import prices and consumer prices is approximately 25 percent (8 percentage points) and 60 percent (7 percentage points) higher, respectively, within the span of one year. This disparity is primarily attributed to an instant shift in the level, indicating that ERPT rises in the same quarter when the euro NEER changes, instead of displaying a divergence over time. These results hold significant implications, given that the regression model, price variables, country set and time sample are consistent across the models. Moreover, the databases underlying the euro NEER computations prove to be highly comparable (see Section 2.5.). The main differences between the two different types of euro NEERs, which can therefore be considered the sources of this variance, are the *country-specific* nature of the euro NEER and the focus on *import* trade flows as opposed to total trade flows.[10]

Figure 15 additionally presents ERPT to aggregate prices after one year for each euro area country in the sample, comparing calculations that utilize euro NEER_I_C with those using the ECB NEER-18.

Finally, Figures 16 and 17 present the point estimates of ERPT to import and consumer prices, respectively, complemented by the 90 percent and 95 percent confidence intervals. The left panels employ the ECB NEER-18 as the exchange rate variable, while the right panels adopt the euro NEER_I_C.

[10] As demonstrated in Section 2.5., the impact of more frequent weights updating is relatively minor. Furthermore, while the country-specific quarterly import-weighted PPI year-on-year growth rate varies across model specifications, it is not influencing the beta coefficients.

Figure 14: Dynamics of ERPT to aggregate prices using self-constructed euro NEER_I_C and ECB's euro NEER_XI




(a) Import deflator

(b) HICP

**Note:** This figure depicts the cumulative sum of the $\beta_k$ coefficients from equation (21) in grey, alongside the cumulative sum of the $\beta_k$ coefficients from equation (6) in green. Note that all NEERs are defined in such a way that an increase represents an appreciation of the domestic currency. By using four lags, the model shows the relationship between euro NEER quarter-on-quarter growth rates and aggregate price quarter-on-quarter growth rates at different horizons within a year. At the annual horizon, this empirical evidence suggests that a 1 percent nominal effective depreciation in the euro raises aggregate import (consumer) prices by, on average, 0.38 (0.18) percent. Previous estimates (depricted in green) suggested an ERPT of 0.30 (0.11).

## 2.7. Discussion

Given that the findings unfold along two dimensions – firstly, the magnitude of the updated ERPT estimates, and secondly, the discrepancy with previous estimates – it is vital to address both aspects in a discussion.

The revised estimates for ERPT to import and consumer prices in the euro area are, on average, 21 percent and 4 percent upon immediate impact, and 38 percent and 18 percent after one year, respectively. For import prices, the derived estimate lies at the lower end of the spectrum reported in literature spanning the last few decades, yet it aligns more closely with the higher values reported in more recent studies. This confirms the common finding of a declining ERPT over time (Arsova, 2021). In particular, several euro area studies have reported a long-run ERPT exceeding 70 percent (Campa & Mínguez, 2006, Faruqee, 2006, Misztal, 2010, Bandt & Razafindrabe, 2014, Cheikh & Rault, 2017, Comunale & Kunovac, 2017). In contrast, other research positions the long-run ERPT between this study's estimate and the higher figures reported in the aforementioned studies (Hahn, 2003, Landolfo, 2007, Gaggl, 2009, Burstein & Gopinath, 2014, Özyurt, 2016). It is noteworthy that recent research suggests a slightly lower ERPT for import prices than this study's estimate, albeit not less than 20 percent (Georgiadis & Gräb & Khalil, 2020, Colavecchio & Rubene, 2020, Ortega & Osbat, 2020, Arsova, 2021). With regard to ERPT to consumer prices, a notable feature is the substantial increase in estimates in comparison to studies utilizing publicly available euro NEERs, which are typically euro NEER_XI. A majority of studies report a short-run ERPT under 5 percent, an observation persisting even in the long run (Faruqee, 2006, Misztal, 2010, Burstein & Gopinath, 2014, Colavecchio &

Table 7: Estimation results of ERPT to aggregate prices using self-constructed euro NEER_I_C

| | Dep. Variable: Import Deflator | Dep. Variable: HICP Goods |
|---|---|---|
| Constant | -0.002*** | 0.001** |
| | (0.001) | (0.000) |
| NEER | -0.211*** | -0.042*** |
| | (0.046) | (0.013) |
| NEER Lag 1 | -0.077** | 0.016* |
| | (0.034) | (0.008) |
| NEER Lag 2 | -0.048*** | -0.041*** |
| | (0.016) | (0.014) |
| NEER Lag 3 | -0.039 | -0.023** |
| | (0.051) | (0.010) |
| NEER Lag 4 | -0.002 | -0.091*** |
| | (0.012) | (0.012) |
| Cum. Sum of NEER Coefficients | -0.377 | -0.181 |
| F-Statistic NEER Lags | 68.726 | 190.484 |
| Output Gap (+4 Lags) | Yes | Yes |
| Trade-Weighted PPI YoY Change (+4 Lags) | Yes | Yes |
| Country Fixed Effects | Yes | Yes |
| Standard Errors | Clustered | Clustered |
| Observations | 910 | 910 |
| R-Squared | 0.580 | 0.255 |
| | Standard Errors in Parentheses | |
| | ***p<0.01, **p<0.05, *p<0.1 | |

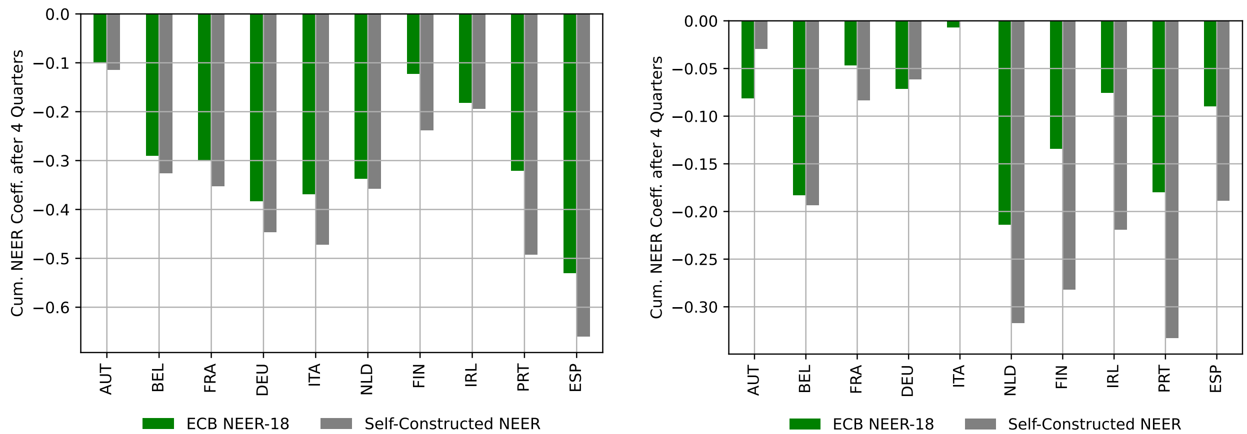
**Note:** This table shows the result of estimating equation (21). The dependent variables are the import deflator and HICP goods, respectively.

Rubene, 2020, Ortega & Osbat, 2020). Conversely, several studies have documented a long-run ERPT ranging between 5 and 10 percent (Schröder & Hüfner, 2002, Hahn, 2003, Landolfo, 2007, Comunale, 2015). It is worth highlighting that the findings from Comunale & Kunovac (2017) closely mirror the magnitude of ERPT to consumer prices after one year as observed in this study.

Furthermore, ERPT to import prices exhibits distinct variations across countries. After one year, Spain records the peak at 66 percent, while Austria records the minimum at 11 percent. Positioned in the lower mid-tier, Finland and Ireland report magnitudes near 20 percent, whereas Belgium, France, and the Netherlands hover in the upper-mid bracket with magnitudes between 32 to 35 percent. Just beneath Spain, Germany, Italy, and Portugal fall into the upper segment with ERPT ranging from 43 to 49 percent.

To contextualize these country-specific results, they are juxtaposed with the three latest studies from Table 1 that evaluate ERPT to import prices over a similar timeframe. The left panel of Table 8 presents ERPT estimates for import prices from Colavecchio & Rubene (2020). Their study uses a euro NEER_I, applying a local projection model that accounts for domestic economic slack and external price pressures, determined by the average export price inflation from the euro area's primary trading partners. Their quarterly data

Figure 15: One year ERPT to aggregate prices for euro area countries using self-constructed euro NEER_I_C and ECB's euro NEER_XI




(a) Import deflator

(b) HICP

**Note:** This figure depicts the cumulative sum of the coefficients $\beta_k$ after four quarters from equation (21) for each of the euro area countries in the sample in grey, alongside the cumulative sum of the coefficients $\beta_k$ after four quarters from equation (6) for each of the euro area countries in the sample in green. Note that all NEERs are defined in such a way that an increase represents an appreciation of the domestic currency.

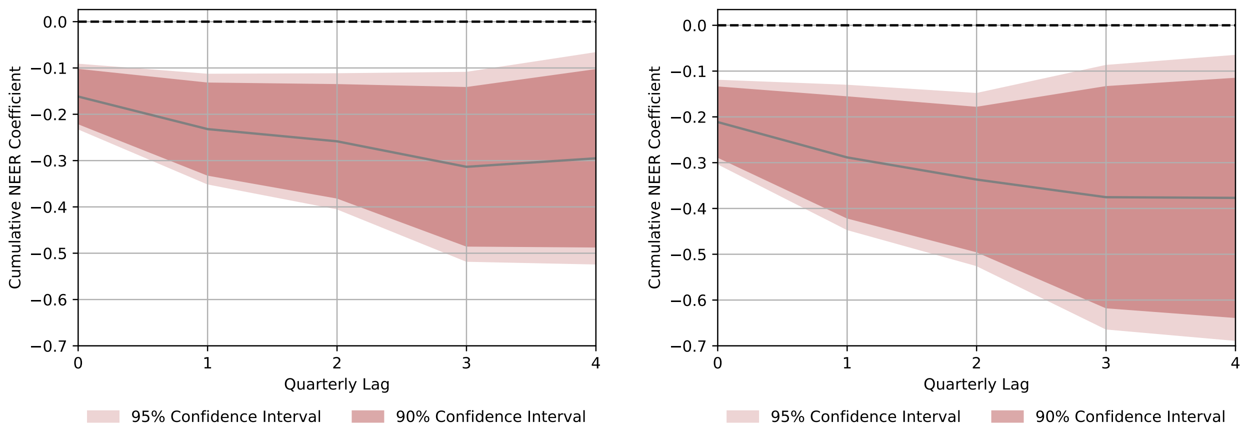
ranges from 1997Q1 to 2019Q1. For import prices, they utilize the total euro area deflator for goods and services, which encompasses intra-euro area trade. In comparison to the present study, Colavecchio & Rubene (2020) differ in their time horizon, exploiting 1997-2019 as opposed to 1999-2022. They also employ a local projections model in contrast to the distributed lag method used here, but with analogous control variables. Notably, their euro NEER, while import-weighted, lacks country-specificity. Both studies utilize identical import deflators. Given these nuances, their approach remains the closest match among studies featured in Table 1.

The euro area ERPT estimates to import prices from both studies align closely, with figures at 33 percent and 38 percent. Both also exhibit similar ranges: Colavecchio & Rubene (2020) highlight Italy with the highest ERPT at 63 percent and Belgium at the lowest with 24 percent. In comparison, this study finds the range spanning from 11 percent (Austria) to 66 percent (Spain). Additionally, both studies identify Italy, Spain, Germany, and Portugal as having the largest coefficients. Both studies show minimal discrepancies in ERPT for France and the Netherlands, and moderate differences for Belgium, Finland, and Ireland. However, Austria's ERPT is significantly divergent, as this study estimates it at a modest 11 percent after a year, while Colavecchio & Rubene (2020) places it notably higher at 45 percent. Overall, ERPT estimates to import prices of the countries under investigation align reasonably well.

Using a NEER_XI in a log-linear regression, Ortega & Osbat (2020) – with data from 1999 to 2017 – report ERPT to import prices ranging between 20 and 50 percent for the countries examined in this study. Notably, their findings also highlight high ERPT values for Spain, Portugal, and Italy.

Thus, it seems to be a robust finding that Spain, Portugal, and Italy have the highest ERPT to import

Figure 16: Dynamics of ERPT to aggregate import prices with confidence intervals




(a) ECB NEER-18 (euro NEER_XI) (b) Self-constructed euro NEER_I_C

**Note:** This figure depicts the cumulative sum of $\beta_k$ coefficients from equations (6) and (21), respectively, alongside the 90 percent and 95 percent confidence intervals. The dependent variable is the import deflator.

prices among the largest euro area countries, with values around or above 50 percent, followed by Germany. Further, it is evident that while other countries have lower ERPT, their magnitudes are still significant.

Arsova (2021), using quarterly data from 1999 to 2018, also notes high ERPT estimates to import prices for Italy and Portugal among the "older euro area member countries". However, these findings are not directly comparable to this study, given the use of the IMF's NEER_XI_C, encompassing all trade partners, not just those external to the euro area.

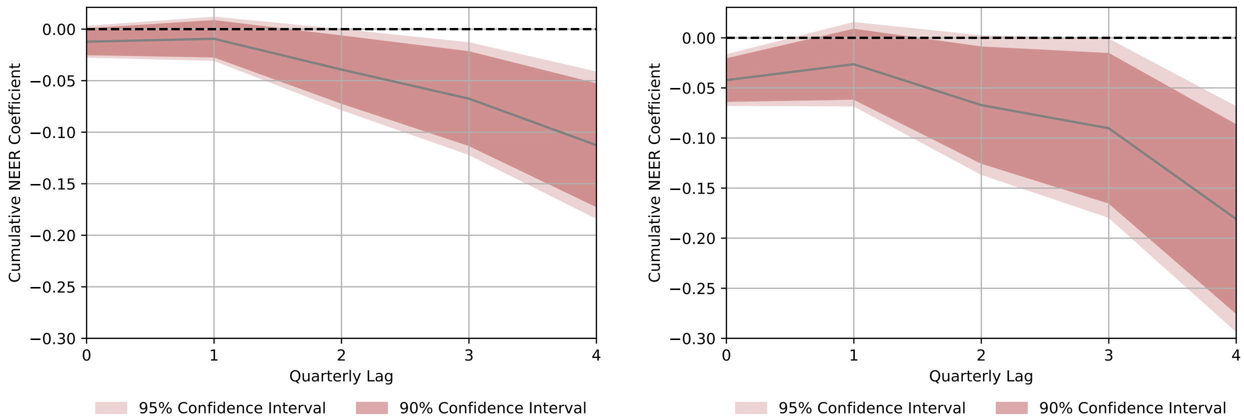
Table 8: Comparison of one year ERPT for the euro area and individual euro area countries: This study vs. Colavecchio & Rubene (2020)

| | Import prices | | | Consumer prices | | |
|---|---|---|---|---|---|---|
| | Colavecchio & Rubene (2020) | Author´s calculations | Difference | Colavecchio & Rubene (2020) | Author´s calculations | Difference |
| EA | 0.33 | 0.38 | -0.05 | 0.04 | 0.18 | -0.14 |
| DEU | 0.54 | 0.44 | 0.10 | 0.06 | 0.06 | 0.00 |
| FRA | 0.34 | 0.35 | -0.01 | 0.03 | 0.08 | -0.05 |
| ITA | 0.63 | 0.47 | 0.16 | 0.05 | 0.00 | 0.05 |
| ESP | 0.54 | 0.66 | -0.12 | 0.09 | 0.18 | -0.09 |
| NLD | 0.38 | 0.35 | 0.03 | 0.05 | 0.31 | -0.26 |
| BEL | 0.24 | 0.31 | -0.07 | 0.05 | 0.19 | -0.14 |
| AUT | 0.45 | 0.11 | 0.34 | 0.09 | 0.02 | 0.07 |
| PRT | 0.50 | 0.49 | 0.01 | 0.05 | 0.34 | -0.29 |
| FIN | 0.35 | 0.23 | 0.12 | 0.08 | 0.28 | -0.20 |
| IRL | 0.30 | 0.19 | 0.11 | 0.06 | 0.22 | -0.16 |

**Note:** This table depicts the degree of ERPT to aggregate import and consumer prices in the euro area as computed by Colavecchio & Rubene (2020) and in this study. The analysis by Colavecchio & Rubene (2020) employs euro NEER_I, whereas this study utilizes NEER_I_C as exchange rate variable.

For this study's ERPT to consumer prices, Italy stands out with zero ERPT, while Portugal stands at the top with 34 percent. Austria has a minimal 3 percent ERPT, with Germany and France at 6 percent and 8 percent, respectively. Belgium, Spain, and Ireland cluster around 20 percent, Finland is at 27 percent,

Figure 17: Dynamics of ERPT to aggregate consumer prices with confidence intervals




(a) ECB NEER-18 (euro NEER_XI)

(b) Self-constructed euro NEER_I_C

**Note:** This figure depicts the cumulative sum of $\beta_k$ coefficients from equations (6) and (21), respectively, alongside the 90 percent and 95 percent confidence intervals. The dependent variable is the HICP goods.

and the Netherlands nears the top with 32 percent.

Most countries, except for Finland and Ireland, display a higher ERPT to import prices than to consumer prices. Finland, Ireland, and the Netherlands present a notable pattern: mid-range ERPT to import prices but upper-range ERPT to consumer prices. Spain and Portugal both exhibit high ERPT values for both import and consumer prices. Austria manifests low ERPT for both categories, while Italy, despite its relatively high ERPT to import prices, records the lowest ERPT to consumer prices. France and Germany show mid-range ERPT to import prices and a lower range for consumer prices. Belgium's ERPT is mid-range for import prices but relatively high for consumer prices. A crucial distinction is that the import prices definition encompasses services, whereas consumer prices focus solely on goods. Given the tendency for services to have a lower ERPT compared to goods, ERPT to consumer prices in this study naturally appears somewhat elevated, whereas the ERPT to import prices seems marginally diminished when compared to other studies or alternative price definitions.

In the right panel of Table 8, estimates of ERPT to consumer price from this study are contrasted with those of Colavecchio & Rubene (2020). The figures from this study tend to be higher, a likely consequence of using the goods HICP for consumer prices, as opposed to Colavecchio & Rubene (2020)'s use of the overall HICP.[11] This choice also yields greater variability in country-specific ERPT estimates, with this study's estimates ranging from 0 to 31 percent, while Colavecchio & Rubene (2020)'s figures lie between 3 and 9 percent. The country-specific ERPT to headline HICP estimated by Ortega & Osbat (2020) seems to align more closely with the lower range presented by Colavecchio & Rubene (2020).

When comparing ERPT estimates to import prices derived from the ECB's NEER_XI with those from self-computed NEER_I_C, the latter consistently surpass the former for all countries. The most pronounced

[11] The goods HICP was selected in this study for consistency with the IMF DOTS data, which focuses solely on goods trade.

gaps, up to 17 percentage points, are evident in Spain, Portugal, Finland, and Italy. In terms of ERPT to consumer prices, notable hikes in estimates are especially visible for Portugal, Spain, Finland, Ireland, and the Netherlands. The difference ranges from roughly 15 percentage points in Ireland, Portugal, and Finland, to around 10 percentage points for Spain and the Netherlands. Modest increases are seen in Belgium and France, while slight decreases are observed for Germany and Italy, with Austria witnessing the steepest decline at 4 percentage points.

As Figure 16 illustrates, ERPT to import prices is significantly different from zero at all quarterly horizons throughout a one-year period. Furthermore, it is also significantly different from 1, implying that the hypothesis of a complete ERPT to import prices can be rejected. Figure 17 demonstrates that in the case of consumer prices, ERPT is significantly different from zero at impact, and then again after two quarters. The span of the confidence intervals serves as a tool for assessing the precision of the estimated values. It is observable that the use of euro NEER_I_C does not result in narrower confidence intervals in comparison to the utilization of the ECB's euro NEER_XI. This observation is consistent in the analysis of ERPT to both import and consumer prices. The observed lack of improved precision may initially appear counterintuitive. However, the discrepancy in precision between the two sets of estimates might be attributed to a model artefact arising from the use of country-specific euro NEERs versus a non country-specific counterpart. As Figure 15 shows, the utilization of country-specific euro NEERs introduces a greater degree of variability in the individual country's estimates. This could potentially be attributed to distinct country characteristics including trade patterns, economic policy divergences, market structures, and fluctuations in domestic and international economic conditions. Consequently, this increased variability in the country estimates widens the confidence intervals. Although employing country-specific euro NEERs offers a richer perspective on individual country dynamics, it seems to add a layer of complexity not fully accommodated by the model, which impacts the precision of the estimates.[12] Correspondingly, the relatively higher precision observed with the non country-specific euro NEER might signal an oversimplification of the economic dynamics at play, potentially missing out on critical country-specific details. As a result, while the widening of confidence intervals goes against the initial economic intuition, it may just be pointing towards a need for further refinement in the model structure to more accurately capture the details introduced by the country-specific euro NEERs. Overall, the estimates using country-specific euro NEERs – despite the apparent decrease in precision – should not be considered inferior, as they provide a more detailed understanding of the complexities inherent in ERPT mechanics.[13] Furthermore, it is essential to note that the narrower confidence intervals when using

[12]While the inclusion of country fixed effects serves to control for unobserved, time-invariant characteristics unique to each country, they may not fully counterbalance the increased variability brought about by the usage of country-specific euro NEERs, as country fixed effects cannot account for more complex, time-variant interdependencies.

[13]To illustrate, imagine you are a soccer coach aiming to assess the performance of each player on your team from previous matches. You have two evaluation methods at your disposal: First, you evaluate every player's performance based on team-wide average metrics, such as running speed, shooting power, and tactical skills. Using these general averages ensures your assessments are consistent across all players, leading to tighter confidence intervals around each performance metric. In the second method, rather than relying on general averages, you assess each player based on metrics specifically tailored to their unique skills, like their individual speed, shooting prowess, and tactical nuances. This approach naturally introduces more variability. Since the criteria are adapted to each player's specific circumstances, the assessments become more nuanced but also exhibit greater variability. As a result, you might observe wider confidence intervals for their performance metrics. However,

NEERs which are not tailored to individual euro area countries might suggest statistical significance more readily compared to when using country-specific NEERs.

Why are the most pronounced differences in ERPT to import prices when using NEER_XI as opposed to NEER_I_C found in Spain, Portugal, Finland, and Italy, and in ERPT to consumer prices, notably in Portugal, Spain, Finland, Ireland, and the Netherlands? Several factors could explain this observation. First, each country in the euro area has its own set of primary trade partners, which might not be perfectly captured by the ECB NEER-18. A country-specific euro NEER would naturally account more accurately for the countries that a particular country trades with most frequently. This could especially be the case for 'peripheral' countries like Spain, Portugal, and Italy, and the euro area's most northern economy, Finland, which might have unique trade relationships that differ from the broader euro area average. Second, countries like Portugal, Spain, and Italy have historically faced unique economic circumstances compared to other euro area countries. This includes factors such as higher unemployment rates, higher levels of public debt, higher levels of inflation, and elevated levels of economic instability. Such structural variations might influence the sensitivity of their economies to exchange rate fluctuations. When using NEER_I_C, these distinctions become more evident. Specifically, the country-specific NEERs are likely to better capture the nuances of each country's trade relationships and economic vulnerabilities, resulting in a more accurate reflection of the pass-through mechanisms. Similarly, individual country characteristics – ranging from their industry composition to the intensity of competition within goods markets to prevalent pricing-to-market strategies and the typical frequency of price adjustments – all play a role in influencing ERPT. In essence, as emphasized by Ortega & Osbat (2020), a multitude of structural factors could explain the heterogeneity in ERPT across euro area countries, such as the structure of the economy, the microeconomic structure and behaviour of firms, and the general macroeconomic environment. When these structural determinants are interlinked with country-specific exchange rate movements, trade patterns, and macroeconomic conditions, adopting country-specific NEERs allows empirical models to more effectively capture these unique attributes. An illustrative example of this is provided by Cheikh & Rault (2017), who highlight that Italy and Spain have a significant presence of industries where full ERPT is observed. This suggests that when the euro's value changes against currencies of key exporters to these countries, the overall ERPT in Italy and Spain might be noticeably affected. Consider a scenario where the euro depreciates against the Russian ruble. Given that Russia has been a significant supplier of oil and raw materials to both Spain and Italy during most of the period under investigation, such a currency movement is likely to drive up import prices in these countries. However, because Russia's overall trade volume with the euro area is relatively small, a euro NEER based on trade flows of the entire euro area might not adequately reflect the impact of the euro's depreciation against the ruble. In contrast, country-specific euro NEERs can better capture these direct and potentially significant effects on Italy and Spain.

despite the broader intervals, this tailored assessment is likely superior as it captures the unique strengths and weaknesses of each player, offering a more precise understanding of individual performance.

## 2.8. Summary and conclusions

This paper investigates the influence of the nominal effective exchange rate (NEER) variable in exchange rate pass-through (ERPT) estimates for aggregate import and consumer prices in the euro area. This subject holds substantial policy relevance given that changes in exchange rates, reflected in aggregate prices, have a direct bearing on the conduct of the ECB's monetary policy.

A significant portion of euro area ERPT studies employ publicly available euro NEERs sourced from well-regarded institutions such as the Bank for International Settlements (BIS), the European Central Bank (ECB), and the International Monetary Fund (IMF) in their investigations. This pertains both to cases where disaggregated data is used – such as data at the firm-, sector-, or country-level – and where data is aggregated at the euro area-level. Those publicly available euro NEERs typically weight nominal bilateral exchange rates based on export and import trade flows of the entire euro area. A basic micro framework for ERPT analyses with NEERs like in Bailliu & Fujii (2004), however, suggests utilizing NEERs where nominal bilateral exchange rates are weighted solely by import trade flows. Furthermore, the heterogeneity of trade patterns exhibited by different countries within the euro area advocates the use of country-specific trade flows, rather than adopting a euro area-wide approach in calculations. In other words, the export patterns of Germany do not have a significant influence on the import and consumer prices within the country, just as the specific import patterns of other euro area countries hold little relevance in this context. This challenges the widespread practice of utilizing publicly available euro NEERs in studies analyzing ERPT to aggregate prices in the euro area. Accordingly, this study harnesses quarterly data from 1999 to 2022 to compute a variety of euro area-wide and country-specific euro NEERs based on IMF DOTS data. These newly created euro NEERs are then incorporated into a distributed lag model, with aggregate price indices as the dependent variable, facilitating a comparison of ERPT estimates across the ten largest euro area countries.

The main findings are multifaceted. First, the utilization of publicly available euro NEERs, sourced from the BIS, ECB, and IMF, results in consistent ERPT estimates. More precisely, the initial impact of ERPT on import and consumer prices is gauged to be, on average, 16 percent and 2 percent, respectively, increasing to 30 percent and 11 percent within the span of one year. Second, reevaluating the ECB's euro NEER using IMF DOTS data, while adhering to the ECB's established methodology, generates an index that closely aligns with the original one. This similarity serves to affirm the credibility of the IMF DOTS data in the context of this analysis. Third, utilizing IMF DOTS data to compute country-specific euro NEERs where nominal bilateral exchange rates are weighted solely by import trade flows unveils significant disparities in the euro NEER across different euro area countries. Consequently, the updated ERPT estimates, which incorporate these alternative euro NEERs, diverge from the initial calculations. Specifically, the revised estimates for ERPT to import and consumer prices are, on average, 21 percent and 4 percent upon immediate impact, and 38 percent and 18 percent after one year, respectively. This implies that ERPT to total import prices and consumer prices is, on average, 25 percent and 60 percent higher respectively compared to evaluations based on publicly available euro NEERs. Fourth, the results imply a disparity in ERPT estimates at the individual country level. Recent euro area studies present findings that align with the observed effects of ERPT on import prices. Specifically, Spain, Portugal and Italy show the highest ERPT to import prices among the largest euro area countries, with values around or above 50 percent, followed by Germany. For most countries, ERPT on goods HICP is both statistically significant and substantial, with Portugal, the Netherlands, Finland, Ireland, Spain, and Belgium standing out, exhibiting rates between 18 percent and 33 percent. Fifth, the use of country-specific euro NEERs where nominal bilateral exchange rates are weighted solely by import trade flows does not result in narrower confidence intervals in comparison to the utilization of the ECB's euro NEER. This may, however, be an artefact of increased variability in the country estimates. To put differently, the country-specific method offers a more nuanced understanding of each country's ERPT but at the cost of higher standard errors. Overall, the findings emphasize that it is critical to carefully consider the choice of the euro NEER when estimating ERPT to aggregate prices, regardless of the methodology, whether it is a distributed lag model, local projection approach, vector autoregression model, or otherwise. The results suggest that one should interpret previous ERPT estimates with caution, given that publicly available euro NEERs are not specifically designed for ERPT analysis.

Further research could look into the qualification of the empirical results obtained in this study. Specifically, a more detailed theoretical examination is required to determine whether the utilization of NEERs, in which nominal bilateral exchange rates are exclusively weighted by import trade flows, holds a comparative advantage in ERPT analysis over NEERs where nominal bilateral exchange rates are weighted considering both export and import trade flows. This is pivotal for deepening the understanding of ERPT both within the euro area and on a global scale.

## 2.9. Appendix

# A Survey of aggregate exchange rate pass-through literature

This section reviews studies that explore aggregate ERPT to import and consumer prices in the euro area, with a particular focus on the temporal and geographical scope, the type of NEER utilized, the model specifications, and some main findings.

As a key study utilizing NEERs in bottom-up approaches, Campa & Mínguez (2006) analyze monthly unit value indices of imports originating from non-euro area countries. Their study encompasses thirteen product categories, predominantly categorized at the one-digit SITC level, across all euro member countries, spanning from January 1989 to March 2001. Their objective is to delineate both category-specific and country-specific ERPT. The database also offers the composition of imports by product category and by country of origin. As the authors state, this detailed breakdown "enables us to undertake a meaningful analysis of differences in pass-through rates across and within countries as arising from the product composition of imports exposed to exchange rate fluctuations" (p.123). The import unit value indices are aggregated on a country-category level, encompassing all products imported from outside the euro area to a specific euro area country, classified under a particular product category. They use the bilateral exchange rate between the domestic currency and the US dollar as the exchange rate measure under the assumption that a single international market for the product category exists. Otherwise, under the assumption that international markets are highly segmented with a significant degree of price discrimination by origin and destination of imports, they use the geometric weighted averages of the bilateral exchange rates of a certain euro area country against its five major non-euro zone providers of imports within the particular product category. These weights are determined by each exporting country's contribution to the total imports of that product category in 1996. Accordingly, they compute and utilize NEER_I_C versions. Their findings indicate that in the euro area, the short-run pass-through rate averages 62 percent, while the estimated long-run rate is 78 percent. Notably, long-run ERPT does not differ significantly across countries or product categories. Furthermore, they show that fluctuations in inflation rates, driven by a uniform euro depreciation, can be substantial, primarily influenced by the individual member countries' varying degrees of openness to imports from countries outside the euro area.

Drawing upon the methodology introduced by Campa & Mínguez (2006), Bandt & Razafindrabe (2014) analyze the impact of currency-invoicing decision of exporting firms on ERPT to import prices in Germany, France, Greece, the Netherlands, Spain and the euro area as a whole. The authors employ monthly import price indices categorized by product category from June 2005 to July 2013. The product classifications exclusively encompass manufacturing sectors, delineated at the 2-digit level according to the EU Classification of Product and Activity. Consistent with the 'segmented market approach' by Campa & Mínguez (2006), a NEER is computed. This NEER represents a weighted average of bilateral exchange rates in relation to the currencies of the United States, the United Kingdom and China. The weights are calculated based on the valuation of imports from the euro area that originate from these countries. Consequently, the exchange rate variable is a euro NEER_I. The authors estimate a fixed effects panel, employing a within estimator for their analysis. Their multi-currency analysis includes nominal bilateral exchange rates and thus allows to distinguish between bilateral ERPT (referring to bilateral euro exchange rates against the currencies of the three aforementioned countries) and multilateral ERPT (referring to the euro NEER_I). The results indicate that multilateral ERPT to import prices is incomplete in the short run but complete (statistically not different from 1) in the long run. Moreover, the authors find that estimates of multilateral ERPT are primarily driven by the euro-dollar bilateral exchange rate.

In another study that builds upon the foundational work by Campa & Mínguez (2006), Cheikh & Rault (2017) analyze ERPT to import prices at a sectoral level, utilizing monthly data from January 1995 to December 2013 for 11 countries in the euro area. The import price data used in this study is organized according to the 1-digit SITC classification, encompassing nine distinct categories for each country. To represent the exchange rate, NEER_XI_C are employed. Utilizing the system generalized method of moments in a dynamic panel data model, where the dependent variable is the import price index specified for each country-sector pair, Cheikh & Rault (2017) find that ERPT is usually less than one across industries. Noteworthy deviations from this observation are the sectors of mineral fuels and raw materials, where the data often fails to reject the hypothesis of full ERPT. Rather than consolidating sector-specific ERPT estimates at the country level, the authors distinguish patterns of ERPT across countries. They observe that Italy and Spain predominantly host industries where full ERPT is a common phenomenon. In contrast, Belgium, Germany, Austria, Finland, and France feature a larger proportion of industries where ERPT appears non-existent. Interestingly, Greece shows significant portions of industries experiencing both full and zero ERPT. Moreover, they identify a notably higher rate of ERPT in the cases of homogeneous goods and commodities like oil and raw materials, compared to differentiated manufactured products such as machinery and transport equipment. Consequently, variations in ERPT across different countries could potentially be attributed to the disparities in the composition of the product composition of imports. To gauge ERPT at the country-level, the authors apply an identical regression model with the import price indices being distinct to each country (instead of being distinct to a country-industry pair). They determine that, on average, short-term ERPT is 64 percent, increasing to 75 percent over the long-term. Furthermore, they observe that the sensitivity of import prices to fluctuations in the exchange rate seems to diminish in a low and more stable inflation environment.

In a recent study, Osbat & Sun & Wagner (2021) assess ERPT to euro area import prices at a sectorally disaggregated level. They analyze data across 28 sectors, categorized according to the NACE Rev.2 classification. The research predominantly employs a vector autoregression model for the analysis, with the majority of the data commencing from 2000. The import price indices used are specific to each sector, while the exchange rate variable utilized is the ECB's euro NEER_XI. Their findings indicate a diverse range of ERPT across various sectors. It is observed that sectors with higher market concentration and higher backward integration in global value chains tend to exhibit a reduced ERPT. Consequently, ERPT shows considerable variation, ranging from nearly full in the case of mining commodities (estimated at around 80 percent) to virtually non-existent for sectors such as beverages, tobacco, and the automotive industry. The authors do not aggregate the sector-specific ERPT to derive an average ERPT figure for the euro area.

In top-down approaches, the categorization by the origin of goods can also be a distinct feature. Nevertheless, this strategy requires comprehensive micro-level data since it necessitates deriving country pair-specific price indices from product-, firm-, or sector-level data. Given that such detailed data is rarely available, only a few studies have managed to integrate country pair-specific price indices into aggregate analysis, with the work of Gopinath et al. (2020) standing out as a notable example. In this study, Gopinath and colleagues use import unit values detailed at the HS 6-digit product level to compute aggregated Fisher price indices at the bilateral country level, applying a distributed lag model across a large set of advanced and emerging economies. They regress the bilateral price indices on the countries' bilateral exchange rate, alongside the importer's dollar exchange rate and an interaction term incorporating both the bilateral and dollar exchange rates and the importing country's dollar invoicing share. Their findings indicate a nearly full pass-through at a one-year horizon, with the dollar exchange rate absorbing most of the effect. Furthermore, they find that a larger dollar invoicing share corresponds to a higher degree of dollar pass-through.

When leveraging aggregate data in top-down approaches, however, the dominant strategy is to employ NEERs as explanatory variable.

Schröder & Hüfner (2002) employ monthly data spanning from 1981 to 2001 to estimate ERPT to consumer prices for five major euro area countries: Germany, France, Italy, Spain, and the Netherlands. Utilizing a vector error correction model, they apply NEERs sourced from the Bank of England, which are NEER_XI_C. The results indicate that the Netherlands experiences the fastest ERPT to consumer prices, although the long-run effects are most pronounced in Italy and France. One year post-adjustment, ERPT to consumer prices fluctuates between 7 percent in France and 12 percent in Italy.

Hahn (2003) analysis ERPT to aggregate prices at various distribution stages, including non-oil import prices and consumer prices, utilizing a vector autoregression model. The study employs euro area-wide data from the second quarter of 1970 to the second quarter of 2002. The exchange rate used in the analysis is the ECB's euro NEER_XI. The study determines an ERPT of 50 percent (after 3 quarters) and 8 percent (after 1 year) for import and consumer prices, respectively.

Faruqee (2006) examines ERPT into a range of aggregate prices with a vector autoregression model. Euro area-wide data is exploited on a monthly level from 1990 through 2002. As in Hahn (2003), this study uses the ECB's euro NEER_XI as explanatory variable. The author establishes that ERPT is 81 percent for import prices and 2 percent for consumer prices, both assessed after a one-year period.

Landolfo (2007) estimates ERPT to import and consumer prices with a dynamic simultaneous equation model. The author uses euro area-wide quarterly data for the period between 1970 and 2003, incorporating the ECB's euro NEER_XI as exchange rate variable. He finds that ERPT to consumer prices is broadly consistent with the results provided by Hahn (2003) in the first year. However, as the timeframe extends, this study finds that ERPT to import prices is marginally lower than what was previously documented by

Hahn (2003).

Shambaugh (2008) decomposes exchange rate changes into different parts and then estimates ERPT to import prices with a vector autoregression model for a large set of industrialized and developing countries. He critically evaluates the conventional methods of measuring macro-level ERPT, pointing out potential inaccuracies and assumptions pertaining to the changes in the exchange rate being perceived as the shocks themselves. The NEER indices applied are NEER_XI_C. The quarterly time sample is 1973 to 1999. He finds that, on average, import prices move quickly and strongly in the same direction as the NEER after each shock (supply, demand, nominal, foreign, and import price shocks). This trend was found to be almost universal, with the United States serving as a prominent exception. Furthermore, the research highlights that the nature of the shock experienced does not hold substantial influence over ERPT estimates when considering import prices. In contrast, ERPT to consumer prices exhibited a varied response to different types of shocks, ranging from almost full to nearly zero.

In the study conducted by Gaggl (2009), the extent of ERPT within the euro area from the inception of the euro until the end of 2007 is examined. Utilizing a vector auto regression method, the author analyzes the impact of ERPT on import and consumer prices, focusing on Austria, Germany, France, Italy, and the Netherlands, in addition to an aggregate analysis of the euro area. The study utilizes monthly data spanning from January 2000 to December 2007, employing Eurostat's euro NEER_XI to represent exchange rates. He identifies a notable ERPT of up to 60 percent in the euro area for import prices. However, the study also points out the challenges in making a cross-country comparison of ERPT to import prices, attributing the difficulty to non-uniformity in the import price measures used. Moreover, the analysis reveals that consumer prices in the euro area remain largely unaffected by fluctuations in the euro NEER_XI, an observation that holds true across individual member countries as well.

In the study conducted by Misztal (2010), ERPT to import and consumer prices in the euro area is scrutinized via a vector autoregression model. The analysis employs data collected on a quarterly basis across the span of nearly a decade, from the first quarter of 1998 to the fourth quarter of 2007. The author employs a euro NEER_XI, although the source of this data is not specified. He finds that, after one year, ERPT to import prices is 75 percent and to consumer prices 2 percent.

In their comprehensive survey, Burstein & Gopinath (2014) examine both short-term and long-term ERPT to import and consumer prices, utilizing aggregate indices for several countries, including Italy, France, and Germany from the euro area. This analysis is performed through a distributed lag regression model, utilizing quarterly data from 1975 to 2011. The authors apply NEER_XI_C in their analysis. Their findings indicate that ERPT to consumer prices remains significantly low across the board, notably lower than ERPT to import prices for each respective country. Specifically, the short-term ERPT into import and consumer prices is found to be as follows: for Italy, 53 percent and -3 percent; for France, 40 percent and 4 percent; and for Germany, 43 percent and -1 percent. Furthermore, the study uncovers that the long-term (two-year) ERPT to import and consumer prices is 53 percent and 1 percent for Italy, 97 percent and 36 percent for France, and 64 percent and -1 percent for Germany. Moreover, the study underscores the necessity for cautious interpretation of cross-country comparisons of these ERPT estimates to import prices, given the varying construction of indices across various countries.

Comunale (2015) constructs a comprehensive multi-variable panel database, which serves as a potential resource for conducting cross-country comparative analyses. In a distributed lag model application of the data from 1994 to 2014 with quarterly frequency for all the euro area members, alongside Eurostat's euro NEER_XI, it is shown that the inclusion of her measures of the financial cycle significantly increases ERPT estimates in the euro area. Particularly, ERPT to consumer prices is around 5 percent in the specification with the regular output gap, but an order of magnitude higher (although still below 10 percent) with her measures of the financial cycle.

In the study conducted by Özyurt (2016), the author examines ERPT to the import prices from outside the euro area, focusing on the aggregate euro area as well as its five major countries, namely France, Germany, Italy, the Netherlands, and Spain. The investigation encompasses the years 1996 to 2015, with data collected at a quarterly frequency. The study employs two different variables for the exchange rate: (i) the ECB's euro NEER_XI, and (ii) the bilateral exchange rate between the euro and the US dollar. Based on a distributed lag regression model, the author finds that ERPT into import prices stemming from fluctuations in the bilateral EUR/USD exchange rate is significantly lower compared to that originating from shifts in the euro NEER_XI. Further, based on the regression with the euro NEER_XI as exchange rate variable, striking heterogeneity in the degree but also in the speed of ERPT is identified. The lowest degree of ERPT to import prices is found for Germany (44 percent after one year) while it is the highest for Italy (116 percent after one year). For the euro area as a whole, EPPT is estimated to be 42 percent after one year.

Comunale & Kunovac (2017) assess ERPT to import and consumer prices for Germany, France, Italy and Spain and the euro area as a whole. They use bayesian vector autoregression models with identification based on a combination of zero and sign restrictions. The data are quarterly covering the years 1992 to 2016. The ECB's euro NEER_XI serves as the exchange rate variable. The findings indicate a substantial ERPT to import prices of 80 percent after one year, contrasted by a markedly smaller ERPT to consumer prices of less than 20 percent after one year within the euro area – an observation corroborated by individual country-level results. Notably, for the ERPT to import prices, Spain and Italy reveal a larger ERPT compared to Germany and France. Furthermore, the authors find that ERPT depends on the composition of shocks underlying fluctuations in the exchange rate. In particular, ERPT is largest when the exchange rate movement is driven by monetary policy and exchange rate shocks, regarding both import and consumer prices.

Georgiadis & Gräb & Khalil (2020) establish a causal link between the rise of global value chain participation and the decline of ERPT to import prices over the last decades. They estimate instrumental variable regressions in a cross-country panel dataset with quarterly data for the time period from 1995 to 2014, encompassing 22 advanced economies. The methodology involves regressing country-specific import price indices on the IMF's NEER_XI_C using adopted trade agreements as instruments for global value chain participation.

They find that ERPT to import prices has been lower in economies whose trading partners exhibit greater global value chain participation. Moreover, they find that ERPT to import prices is on average 30 percent.

Colavecchio & Rubene (2020) investigate non-linearities in ERPT to import and consumer prices in all 19 euro area countries as well as the euro area as a whole with quarterly data from 1997 to 2019. They employ a euro NEER_I as exchange rate variable, "since we think that it is more appropriate [than a NEER_XI] when analysing import and consumer prices" (p.9). Using a local projection model, the authors determine that both consumer and import prices in the euro area exhibit significant reactions to fluctuations in exchange rates after a one-year period, with responses noted at 4 percent and 33 percent, respectively. The extent of this reaction tends to increase with larger shifts in the exchange rate, but the extent of ERPT appears to be symmetric for depreciations and appreciations. Accordingly, they conclude that the magnitude, rather than the direction, of exchange rate fluctuations affect the degree of ERPT to import and consumer prices in the euro area. Furthermore, they note that ERPT is not uniform across different countries in the euro area, with disparities evident both in the type of prices (import or consumer) and the degree of exchange rate changes that trigger price responses.

Supplementing a literature review on ERPT, Ortega & Osbat (2020) produce empirical estimates for both the euro area as a whole and its individual members. They use quarterly data from 1999 to 2017 and apply a log-linear regression model with NEER_XI_C as key explanatory variable. They find that, within the span of a year, ERPT in the euro area and its member countries is, on average, 30 percent to import prices and 4 percent to consumer prices. These results are noted to be at the lower end of the spectrum in comparison to other findings documented in the literature. Furthermore, they observed a higher degree of variation in ERPT relating to import prices across different countries, as opposed to ERPT variation relating to consumer prices.

Arsova (2021) estimates short- and long-run ERPT to import prices in 19 European countries with quarterly data covering the years 1999 to 2018. Moreover, she tests the existence of a long-run equilibrium relationship between import prices and the nominal exchange rate. The IMF's NEER_XI_C, weighted by the unit labour costs of a country's trading partners, serves as the exchange rate variable in the analysis. Notably, this NEER_XI_C is based on trade flows with all trade partners, and not only with those outside the euro area. By employing panel cointegration tests, she finds that a long-run equilibrium relationship between import prices and the nominal exchange rate exists. Subsequent evaluations using multiple panel estimators, including a panel autoregressive distributed-lag model, reveal that ERPT is roughly 20 percent in the short-run and increases to about 35 percent in the long-run. The study also unveils a discrepancy in ERPT values across the EU, with 'core' nations like Austria, Belgium, France, and the Netherlands facing low to non-significant ERPT, in contrast to the 'peripheral' countries such as Portugal, where ERPT is found to be high or even fully realized. Interestingly, Germany deviates from this pattern, exhibiting a statistically significant long-term ERPT of 56 percent, while Spain presents an estimated coefficient that lacks statistical significance.

# B Data

**Sample Countries**

Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain

**Time Period**

1999Q1 - 2022Q4 if not defined differently

**ECB's Group of 18 Partner Countries**

Australia, Canada, Denmark, Hong Kong, Japan, Rep. of Korea, Norway, Singapore, Sweden, Switzerland, United Kingdom, United States (NEER-12 group of partner countries)

+ Bulgaria, China, Czech Rep., Hungary, Poland, Romania (NEER-18 group of partner countries)

**Sources and Definitions of Variables**

*Dependent variables*:

- Harmonised Index of Consumer Prices (HICP) - Goods, monthly index (2015=100). Source: ECB Statistical Data Warehouse. Calculated as the quarter-on-quarter growth rate in the level of the average quarterly HICP.

- Imports of goods and services deflator (national accounts basis), monthly index (national reference year). Source: OECD Economic Outlook Database. Calculated as the quarter-on-quarter growth rate in the level of the average quarterly imports deflator.

*Explanatory and other variables*:

- Gross domestic product, real, seasonally adjusted, domestic currency. Source: IMF International Financial Statistics. Calculated as the quarterly output gap with a smoothing parameter lambda of 1,600 for HP-filtering.

- Nominal bilateral US dollar exchange rates, monthly data. Source: IMF International Financial Statistics. Used to calculate nominal bilateral exchange rate matrix.

- Nominal effective exchange rate (NEER), monthly index (2020=100), computed against a group of up to 64 trading partners (broad index). Source: BIS Statistics Warehouse. Calculated as the quarter-on-quarter growth rate in the level of the average quarterly NEER.

- Nominal effective exchange rate, monthly index (1999Q1=100), computed against a group of 18 trading partners (ECB NEER-18). Source: ECB Statistical Data Warehouse. Calculated as the quarter-on-quarter growth rate in the level of the average quarterly NEER.

- Nominal effective exchange rate, monthly index (2015=100), computed against a group of up to 31 trading partners. Source: IMF International Financial Statistics. Calculated as the quarter-on-quarter growth rate in the level of the average quarterly NEER.

- Origin of value added in final demand by source country and industry in US dollar, yearly data. Source: OECD Trade in Value Added database. Used to calculate the share of each country's total supply as a result of its own domestic production.

- Producer prices, monthly index (2015=100), manufacturing, domestic producer prices. Source: OECD Main Economic Indicators. Country coverage: Sample countries except for Austria + Czech Rep., Denmark, Hungary, Japan, Rep. of Korea, Norway, Poland, Sweden, United Kingdom. Calculated as the year-on-year growth rate in the level of the average quarterly producer price index.

- Producer prices, monthly index (2015=100), manufacturing, total producer prices. Source: OECD Main Economic Indicators. Country coverage: Australia, Canada, United States. Calculated as the year-on-year growth rate in the level of the average quarterly producer price index.

- Producer prices, monthly index (2010=100), all commodities, total producer prices. Source: IMF International Financial Statistics. Country coverage: Austria, Bulgaria, Hong Kong, Romania, Switzerland. Calculated as the year-on-year growth rate in the level of the average quarterly producer price index.

- Producer prices, monthly index (2018=100), manufacturing, total producer prices. Source: Department of Statistics Singapore. Country coverage: Singapore. Calculated as the year-on-year growth rate in the level of the average quarterly producer price index.

- Producer prices, quarterly data, growth rate same period previous year, industrial activities, total producer prices. Source: OECD Main Economic Indicators. Country coverage: China.

- Value of exports - Goods, free on board, US Dollars. Source: IMF Direction of Trade Statistics. Used to calculate trade weights.

- Value of imports - Goods, cost, insurance, freight, US Dollars. Source: IMF Direction of Trade Statistics. Used to calculate trade weights.[14]

# C Supplementary Figures and Tables

Tables 9 to 11 present the trade weights underlying the euro NEER_XI of the ECB, BIS and IMF, respectively. The BIS and IMF trade weights have been adjusted to total one over the 18 partner countries as defined by the ECB in its NEER-18. Accordingly, these weights underlie the trade-weighted PPI control variable

[14] IMF DOTS also offers data on the "Value of Imports, Free on board". This series is, however, not as comprehensive as the "Value of Imports, Cost, Insurance, Freight" series: For the latter, DOTS offers more than 14 million observations and for the former, DOTS offers less than 1 million observations.

in equation (6). The 'non-adjusted sum' column indicates the summation of the non-adjusted trade weights across these 18 partner countries. The color gradient from dark green to dark red represents the highest to lowest values, respectively.

Tables 12 and 13 present the trade weights underlying the NEER_XI_C (incorporating intra-euro area trade) of the BIS and IMF, respectively. The trade weights have been adjusted to total one over the 19 euro area partner countries + 18 partner countries outside the euro area as defined by the ECB in its NEER-18. Accordingly, these weights underlie the trade-weighted PPI control variable in equation (21). The 'non-adjusted sum' column indicates the summation of the unadjusted trade weights across these 37 partner countries. The color gradient from dark green to dark red represents the highest to lowest values, respectively.

Tables 14 and 15 show the regression results of equation (21), i.e. utilizing the country-specific euro NEERs (incorporating intra-euro area trade) provided by the BIS and IMF as explanatory variables.

Tables 16 through 22 detail the calculations used to determine the overall trade weights of the self-constructed euro NEER_XI. These calculations utilize data from IMF DOTS and OECD TiVA, and the resulting euro NEER is designed to be comparable to the ECB's officially published NEER-18. Take for example Table 16, which shows the overall trade weight calculation for the euro NEER_XI in 1999-2000: The row titled "Euro area exports" reveals the simple share of euro area exports that go to each of the 18 partner countries, plus the aggregate for the rest of the world. For example, 1.1 percent of euro area exports go to Australia, 0.3 percent to Bulgaria, 1.4 percent to Canada, etc. The main diagonal of the supply structure matrix shows what portion of each country's total supply is a result of its own domestic production. For example, 49.1 percent of Australia's total supply stems from domestic production, 40.7 percent of Bulgaria's total supply stems from domestic production, 35.8 percent of Canada's total supply stems from domestic production, etc. The remaining matrix entries in each column account for the proportion of imports from each partner country. For example, in Australia, 49.1 percent of total supply stems from domestic production, while 1.4 percent is accounted for by imports from Canada, 1 percent by imports from Hong Kong, etc, with all these percentages totalling to 100. Double export weights are calculated by multiplying each row of the supply structure matrix by the simple euro area export shares, following equation (15). For example, the double export weight of 1.5 percent assigned to Australia is obtained as follows: $(0.011 \times 0.491) + (0.003 \times 0.003) + (0.014 \times 0.003) + ... + (0.283 \times 0.019)$. This double export weight measures the competition faced by euro area exporters from Australian producers in both the Australian market as well as in all of the other foreign markets. Put differently, this weight quantifies the competition faced by euro area exporters from Australian producers both within Australia and in other markets. Of Australia's 1.5 percent double export weight, only 0.5 percentage points ($=0.011 \times 0.491$) are attributed to competition in the Australian market, the remainder arises from competition in third markets. Finally, the overall trade weights are computed by multiplying the double export weights by the euro area export share and adding the product of import weights and the euro area import share. For example, Australia's overall trade weight of 0.012 is computed as: (0.015 x 0.497) + (0.008 x 0.503).

Table 9: Trade weights by partner country underlying the ECB NEER-18

| Group | Country Name | 1999-2000 | 2001-2003 | 2004-2006 | 2007-2009 | 2010-2012 | 2013-2015 | 2016-2022 |
|---|---|---|---|---|---|---|---|---|
| ECB NEER-18 Trade Partners | Australia | 0.009 | 0.009 | 0.010 | 0.011 | 0.012 | 0.011 | 0.010 |
| | Bulgaria | 0.003 | 0.004 | 0.006 | 0.006 | 0.006 | 0.006 | 0.007 |
| | Canada | 0.020 | 0.020 | 0.020 | 0.019 | 0.019 | 0.018 | 0.018 |
| | China, P.R.: Hong Kong | 0.034 | 0.033 | 0.031 | 0.026 | 0.026 | 0.026 | 0.023 |
| | China, P.R.: Mainland | 0.049 | 0.069 | 0.103 | 0.138 | 0.168 | 0.176 | 0.177 |
| | Czech Rep. | 0.025 | 0.031 | 0.038 | 0.044 | 0.044 | 0.043 | 0.046 |
| | Denmark | 0.028 | 0.029 | 0.029 | 0.029 | 0.025 | 0.024 | 0.024 |
| | Hungary | 0.022 | 0.025 | 0.028 | 0.029 | 0.026 | 0.027 | 0.028 |
| | Japan | 0.091 | 0.080 | 0.072 | 0.063 | 0.059 | 0.048 | 0.049 |
| | Korea, Rep. of | 0.026 | 0.028 | 0.033 | 0.033 | 0.032 | 0.031 | 0.030 |
| | Norway | 0.016 | 0.015 | 0.017 | 0.018 | 0.016 | 0.015 | 0.013 |
| | Poland, Rep. of | 0.030 | 0.034 | 0.044 | 0.056 | 0.058 | 0.060 | 0.065 |
| | Romania | 0.008 | 0.011 | 0.015 | 0.018 | 0.019 | 0.021 | 0.023 |
| | Singapore | 0.021 | 0.022 | 0.019 | 0.021 | 0.022 | 0.021 | 0.022 |
| | Sweden | 0.049 | 0.044 | 0.046 | 0.045 | 0.043 | 0.041 | 0.039 |
| | Switzerland | 0.086 | 0.085 | 0.080 | 0.082 | 0.084 | 0.079 | 0.074 |
| | United Kingdom | 0.225 | 0.218 | 0.204 | 0.172 | 0.156 | 0.158 | 0.152 |
| | United States | 0.259 | 0.244 | 0.206 | 0.191 | 0.186 | 0.196 | 0.200 |
| | **Sum** | **1** | **1** | **1** | **1** | **1** | **1** | **1** |

Table 10: Trade weights by partner country underlying the BIS's (broad) euro NEER_XI

| Group | Country Name | 1999-2001 | 2002-2004 | 2005-2007 | 2008-2010 | 2011-2013 | 2014-2016 | 2017-2022 |
|---|---|---|---|---|---|---|---|---|
| ECB NEER-18 Trade Partners | Australia | 0.008 | 0.009 | 0.009 | 0.009 | 0.010 | 0.008 | 0.008 |
| | Bulgaria | 0.004 | 0.005 | 0.006 | 0.006 | 0.007 | 0.007 | 0.008 |
| | Canada | 0.020 | 0.019 | 0.019 | 0.017 | 0.017 | 0.016 | 0.016 |
| | China, P.R.: Hong Kong | 0.007 | 0.005 | 0.004 | 0.004 | 0.004 | 0.004 | 0.003 |
| | China, P.R.: Mainland | 0.070 | 0.108 | 0.154 | 0.203 | 0.228 | 0.231 | 0.238 |
| | Czech Rep. | 0.033 | 0.041 | 0.047 | 0.052 | 0.052 | 0.054 | 0.058 |
| | Denmark | 0.028 | 0.028 | 0.027 | 0.025 | 0.022 | 0.021 | 0.021 |
| | Hungary | 0.028 | 0.032 | 0.033 | 0.031 | 0.029 | 0.032 | 0.034 |
| | Japan | 0.107 | 0.093 | 0.080 | 0.073 | 0.067 | 0.056 | 0.056 |
| | Korea, Rep. of | 0.030 | 0.033 | 0.038 | 0.036 | 0.036 | 0.035 | 0.035 |
| | Norway | 0.014 | 0.014 | 0.015 | 0.015 | 0.013 | 0.011 | 0.010 |
| | Poland, Rep. of | 0.037 | 0.045 | 0.053 | 0.064 | 0.064 | 0.068 | 0.074 |
| | Romania | 0.011 | 0.016 | 0.019 | 0.022 | 0.023 | 0.025 | 0.028 |
| | Singapore | 0.020 | 0.018 | 0.017 | 0.016 | 0.017 | 0.015 | 0.015 |
| | Sweden | 0.051 | 0.050 | 0.049 | 0.044 | 0.043 | 0.038 | 0.037 |
| | Switzerland | 0.075 | 0.076 | 0.071 | 0.075 | 0.074 | 0.069 | 0.066 |
| | United Kingdom | 0.213 | 0.197 | 0.171 | 0.138 | 0.127 | 0.131 | 0.116 |
| | United States | 0.244 | 0.212 | 0.187 | 0.170 | 0.168 | 0.180 | 0.179 |
| | **Sum** | **1** | **1** | **1** | **1** | **1** | **1** | **1** |
| | **Sum (non-adjusted)** | **0.819** | **0.816** | **0.804** | **0.791** | **0.780** | **0.793** | **0.796** |

Table 11: Trade weights by partner country underlying the IMF's euro NEER_XI

| Group | Country Name | 1999-2003 | 2004-2006 | 2007-2009 | 2010-2012 | 2013-2015 | 2016-2022 |
|---|---|---|---|---|---|---|---|
| ECB NEER-18 Trade Partners | Australia | NaN | 0.020 | 0.020 | 0.021 | 0.018 | 0.017 |
| | Bulgaria | NaN | NaN | NaN | NaN | NaN | 0.007 |
| | Canada | 0.027 | 0.030 | 0.027 | 0.025 | 0.025 | 0.024 |
| | China, P.R.: Hong Kong | NaN | NaN | NaN | NaN | NaN | NaN |
| | China, P.R.: Mainland | 0.071 | 0.121 | 0.162 | 0.215 | 0.232 | 0.240 |
| | Czech Rep. | 0.024 | 0.033 | 0.038 | 0.030 | 0.026 | 0.025 |
| | Denmark | 0.027 | 0.024 | 0.024 | 0.019 | 0.019 | 0.019 |
| | Hungary | 0.023 | 0.022 | 0.021 | 0.018 | 0.015 | 0.013 |
| | Japan | 0.115 | 0.085 | 0.074 | 0.074 | 0.065 | 0.064 |
| | Korea, Rep. of | 0.034 | 0.039 | 0.041 | 0.046 | 0.049 | 0.047 |
| | Norway | NaN | 0.018 | 0.020 | 0.016 | 0.015 | 0.013 |
| | Poland, Rep. of | 0.036 | 0.047 | 0.059 | 0.056 | 0.055 | 0.057 |
| | Romania | NaN | 0.017 | 0.022 | 0.020 | 0.021 | 0.023 |
| | Singapore | 0.021 | 0.017 | 0.016 | 0.017 | 0.017 | 0.019 |
| | Sweden | 0.050 | 0.047 | 0.045 | 0.042 | 0.036 | 0.034 |
| | Switzerland | 0.075 | 0.050 | 0.055 | 0.061 | 0.055 | 0.052 |
| | United Kingdom | 0.217 | 0.172 | 0.145 | 0.117 | 0.120 | 0.108 |
| | United States | 0.280 | 0.259 | 0.231 | 0.223 | 0.233 | 0.239 |
| | **Sum** | **1** | **1** | **1** | **1** | **1** | **1** |
| | **Sum (non-adjusted)** | **0.851** | **0.761** | **0.733** | **0.729** | **0.733** | **0.750** |

Table 12: Trade weights by partner country underlying the BIS's (broad) NEER_XI_C (incorporating intra-euro area trade), 2017-2022

| Group | Country Name | AUT | BEL | FIN | FRA | DEU | IRL | ITA | NLD | PRT | ESP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Euro Area Trade Partners | Austria | NaN | 0.014 | 0.016 | 0.018 | 0.045 | 0.009 | 0.027 | 0.016 | 0.013 | 0.015 |
| | Belgium | 0.024 | NaN | 0.030 | 0.056 | 0.042 | 0.042 | 0.042 | 0.077 | 0.034 | 0.036 |
| | Croatia, Rep. of | 0.007 | 0.002 | 0.001 | 0.001 | 0.003 | 0.001 | 0.005 | 0.002 | 0.001 | 0.001 |
| | Cyprus | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 |
| | Estonia, Rep. of | 0.001 | 0.001 | 0.028 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 |
| | Finland | 0.005 | 0.007 | NaN | 0.006 | 0.010 | 0.004 | 0.006 | 0.011 | 0.005 | 0.006 |
| | France | 0.050 | 0.114 | 0.051 | NaN | 0.083 | 0.078 | 0.105 | 0.068 | 0.118 | 0.143 |
| | Germany | 0.347 | 0.192 | 0.210 | 0.207 | NaN | 0.132 | 0.203 | 0.230 | 0.192 | 0.195 |
| | Greece | 0.003 | 0.003 | 0.002 | 0.003 | 0.003 | 0.003 | 0.007 | 0.003 | 0.003 | 0.004 |
| | Ireland | 0.008 | 0.050 | 0.009 | 0.018 | 0.017 | NaN | 0.014 | 0.023 | 0.011 | 0.014 |
| | Italy | 0.073 | 0.064 | 0.044 | 0.093 | 0.069 | 0.037 | NaN | 0.052 | 0.075 | 0.096 |
| | Latvia | 0.001 | 0.001 | 0.005 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 |
| | Lithuania | 0.002 | 0.002 | 0.009 | 0.002 | 0.003 | 0.001 | 0.002 | 0.003 | 0.002 | 0.002 |
| | Luxembourg | 0.002 | 0.008 | 0.002 | 0.004 | 0.003 | 0.001 | 0.002 | 0.003 | 0.002 | 0.002 |
| | Malta | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 |
| | Netherlands, The | 0.041 | 0.114 | 0.058 | 0.055 | 0.066 | 0.045 | 0.053 | NaN | 0.055 | 0.053 |
| | Portugal | 0.006 | 0.007 | 0.005 | 0.016 | 0.010 | 0.005 | 0.009 | 0.008 | NaN | 0.055 |
| | Slovak Rep. | 0.023 | 0.007 | 0.007 | 0.012 | 0.017 | 0.004 | 0.013 | 0.008 | 0.008 | 0.011 |
| | Slovenia, Rep. of | 0.013 | 0.003 | 0.003 | 0.004 | 0.007 | 0.002 | 0.008 | 0.003 | 0.003 | 0.004 |
| | Spain | 0.024 | 0.035 | 0.024 | 0.075 | 0.040 | 0.024 | 0.058 | 0.033 | 0.264 | NaN |
| | **Intermediate Sum** | **0.629** | **0.625** | **0.506** | **0.570** | **0.422** | **0.389** | **0.559** | **0.545** | **0.786** | **0.638** |
| ECB NEER-18 Trade Partners | Australia | 0.004 | 0.003 | 0.006 | 0.003 | 0.004 | 0.004 | 0.005 | 0.004 | 0.001 | 0.003 |
| | Bulgaria | 0.004 | 0.003 | 0.001 | 0.002 | 0.004 | 0.001 | 0.005 | 0.002 | 0.001 | 0.002 |
| | Canada | 0.006 | 0.010 | 0.008 | 0.007 | 0.008 | 0.016 | 0.009 | 0.006 | 0.004 | 0.006 |
| | China, P.R.: Hong Kong | 0.000 | 0.003 | 0.000 | 0.003 | 0.001 | 0.001 | 0.004 | 0.001 | 0.000 | 0.001 |
| | China, P.R.: Mainland | 0.080 | 0.054 | 0.113 | 0.122 | 0.149 | 0.100 | 0.109 | 0.116 | 0.049 | 0.109 |
| | Czech Rep. | 0.036 | 0.013 | 0.016 | 0.016 | 0.041 | 0.008 | 0.017 | 0.017 | 0.009 | 0.018 |
| | Denmark | 0.005 | 0.007 | 0.024 | 0.006 | 0.012 | 0.006 | 0.006 | 0.012 | 0.005 | 0.006 |
| | Hungary | 0.022 | 0.008 | 0.007 | 0.009 | 0.023 | 0.003 | 0.012 | 0.009 | 0.007 | 0.011 |
| | Japan | 0.018 | 0.030 | 0.024 | 0.027 | 0.033 | 0.036 | 0.025 | 0.031 | 0.010 | 0.019 |
| | Korea, Rep. of | 0.011 | 0.011 | 0.018 | 0.013 | 0.020 | 0.015 | 0.017 | 0.016 | 0.009 | 0.014 |
| | Norway | 0.003 | 0.003 | 0.018 | 0.003 | 0.005 | 0.004 | 0.003 | 0.009 | 0.002 | 0.004 |
| | Poland, Rep. of | 0.027 | 0.019 | 0.030 | 0.022 | 0.050 | 0.009 | 0.027 | 0.024 | 0.015 | 0.021 |
| | Romania | 0.013 | 0.006 | 0.005 | 0.010 | 0.016 | 0.002 | 0.020 | 0.006 | 0.005 | 0.008 |
| | Singapore | 0.003 | 0.013 | 0.004 | 0.009 | 0.008 | 0.006 | 0.005 | 0.013 | 0.003 | 0.003 |
| | Sweden | 0.010 | 0.022 | 0.098 | 0.012 | 0.017 | 0.006 | 0.011 | 0.020 | 0.008 | 0.009 |
| | Switzerland | 0.040 | 0.019 | 0.013 | 0.028 | 0.040 | 0.025 | 0.034 | 0.014 | 0.011 | 0.021 |
| | United Kingdom | 0.024 | 0.059 | 0.037 | 0.055 | 0.051 | 0.120 | 0.042 | 0.064 | 0.040 | 0.051 |
| | United States | 0.063 | 0.094 | 0.072 | 0.083 | 0.094 | 0.250 | 0.090 | 0.092 | 0.034 | 0.057 |
| | **Total Sum** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** |
| | **Sum (non-adjusted)** | **0.929** | **0.887** | **0.879** | **0.895** | **0.884** | **0.920** | **0.875** | **0.895** | **0.926** | **0.873** |

Table 13: Trade weights by partner country underlying the IMF's NEER_XI_C (incorporating intra-euro area trade), 2016-2022

| Group | Country Name | AUT | BEL | FIN | FRA | DEU | IRL | ITA | NLD | PRT | ESP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro Area Trade Partners** | Austria | NaN | 0.015 | 0.014 | 0.015 | 0.040 | 0.008 | 0.023 | 0.018 | 0.012 | 0.014 |
| | Belgium | 0.018 | NaN | 0.023 | 0.036 | 0.030 | 0.017 | 0.031 | 0.019 | 0.025 | 0.027 |
| | Croatia, Rep. of | 0.007 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 0.014 | NaN |
| | Cyprus | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | Estonia, Rep. of | NaN | NaN | 0.019 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | Finland | 0.006 | 0.008 | NaN | 0.006 | 0.010 | NaN | NaN | 0.010 | NaN | 0.006 |
| | France | 0.050 | 0.100 | 0.050 | NaN | 0.084 | 0.073 | 0.100 | 0.082 | 0.107 | 0.131 |
| | Germany | 0.327 | 0.209 | 0.204 | 0.208 | NaN | 0.138 | 0.197 | 0.225 | 0.171 | 0.189 |
| | Greece | NaN | NaN | NaN | NaN | NaN | NaN | 0.007 | NaN | 0.026 | NaN |
| | Ireland | 0.008 | 0.014 | 0.009 | 0.022 | 0.017 | NaN | 0.013 | 0.020 | 0.014 | 0.015 |
| | Italy | 0.070 | 0.080 | 0.043 | 0.092 | 0.074 | 0.040 | NaN | 0.074 | 0.063 | 0.096 |
| | Latvia | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | Lithuania | NaN | NaN | 0.008 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | Netherlands, The | 0.030 | 0.027 | 0.041 | 0.042 | 0.047 | 0.033 | 0.042 | NaN | 0.041 | 0.043 |
| | Portugal | NaN | 0.008 | NaN | 0.013 | 0.009 | NaN | 0.009 | 0.009 | NaN | 0.046 |
| | Slovak Rep. | 0.014 | 0.006 | 0.006 | 0.008 | 0.012 | NaN | 0.010 | 0.007 | NaN | 0.008 |
| | Slovenia, Rep. of | 0.009 | NaN | NaN | NaN | NaN | NaN | 0.006 | NaN | NaN | NaN |
| | Spain | 0.024 | 0.039 | 0.025 | 0.069 | 0.041 | 0.025 | 0.055 | 0.042 | 0.192 | NaN |
| | **Intermediate Sum** | **0.563** | **0.507** | **0.442** | **0.511** | **0.364** | **0.334** | **0.492** | **0.507** | **0.664** | **0.573** |
| **ECB NEER-18 Trade Partners** | Australia | 0.007 | 0.008 | 0.010 | 0.006 | 0.008 | 0.007 | 0.008 | 0.008 | NaN | 0.007 |
| | Bulgaria | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | Canada | 0.010 | 0.012 | 0.013 | 0.011 | 0.012 | 0.015 | 0.013 | 0.011 | 0.011 | 0.011 |
| | China, P.R.: Hong Kong | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| | China, P.R.: Mainland | 0.089 | 0.118 | 0.124 | 0.125 | 0.161 | 0.106 | 0.126 | 0.096 | 0.079 | 0.111 |
| | Czech Rep. | 0.034 | 0.017 | 0.018 | 0.018 | 0.038 | 0.011 | 0.019 | 0.019 | 0.012 | 0.019 |
| | Denmark | 0.007 | 0.011 | 0.023 | 0.007 | 0.013 | 0.007 | 0.008 | 0.014 | 0.008 | 0.008 |
| | Hungary | 0.020 | 0.009 | 0.009 | 0.010 | 0.020 | NaN | 0.012 | 0.010 | 0.008 | 0.011 |
| | Japan | 0.023 | 0.032 | 0.030 | 0.033 | 0.038 | 0.045 | 0.032 | 0.027 | 0.017 | 0.026 |
| | Korea, Rep. of | 0.017 | 0.017 | 0.024 | 0.019 | 0.026 | 0.018 | 0.023 | 0.027 | 0.013 | 0.018 |
| | Norway | NaN | NaN | 0.018 | NaN | 0.006 | NaN | NaN | 0.008 | NaN | NaN |
| | Poland, Rep. of | 0.033 | 0.030 | 0.035 | 0.026 | 0.049 | 0.014 | 0.032 | 0.033 | 0.020 | 0.026 |
| | Romania | 0.016 | 0.009 | 0.006 | 0.011 | 0.016 | NaN | 0.019 | 0.010 | 0.008 | 0.010 |
| | Singapore | 0.006 | 0.009 | 0.006 | 0.014 | 0.010 | 0.010 | 0.008 | 0.010 | NaN | 0.006 |
| | Sweden | 0.013 | 0.022 | 0.089 | 0.015 | 0.021 | 0.011 | 0.013 | 0.025 | 0.012 | 0.012 |
| | Switzerland | 0.045 | 0.021 | 0.017 | 0.031 | 0.042 | 0.034 | 0.037 | 0.021 | 0.017 | 0.024 |
| | United Kingdom | 0.032 | 0.074 | 0.043 | 0.059 | 0.058 | 0.112 | 0.048 | 0.081 | 0.065 | 0.058 |
| | United States | 0.084 | 0.105 | 0.094 | 0.105 | 0.118 | 0.276 | 0.110 | 0.091 | 0.065 | 0.080 |
| | **Total Sum** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** |
| | **Sum (non-adjusted)** | **0.918** | **0.865** | **0.860** | **0.871** | **0.873** | **0.923** | **0.863** | **0.877** | **0.873** | **0.848** |

Table 14: Estimation results of ERPT to aggregate import prices using NEER_XI_C (incorporating intra-euro area trade) provided by BIS and IMF as exchange rate variable

| | Dependent Variable: Import Deflator | |
|---|---|---|
| | BIS country-specific NEER | IMF country-specific NEER |
| Constant | -0.001*** | -0.001*** |
| | (0.000) | (0.000) |
| NEER | -0.309*** | -0.284*** |
| | (0.065) | (0.056) |
| NEER Lag 1 | -0.091** | -0.089** |
| | (0.045) | (0.036) |
| NEER Lag 2 | -0.039 | -0.036* |
| | (0.024) | (0.020) |
| NEER Lag 3 | -0.019 | -0.024 |
| | (0.053) | (0.047) |
| NEER Lag 4 | 0.013 | 0.008 |
| | (0.031) | (0.026) |
| Cum. Sum of NEER Coefficients | -0.445 | -0.425 |
| F-Statistic NEER Lags | 27.556 | 34.562 |
| Output Gap (+4 Lags) | Yes | Yes |
| Trade-Weighted PPI YoY Change (+4 Lags) | Yes | Yes |
| Country Fixed Effects | Yes | Yes |
| Standard Errors | Clustered | Clustered |
| Observations | 910 | 910 |
| R-Squared | 0.602 | 0.600 |
| | Standard Errors in Parentheses | |
| | ***p<0.01, **p<0.05, *p<0.1 | |

Table 15: Estimation results of ERPT to aggregate consumer prices using NEER_XI_C (incorporating intra-euro area trade) provided by BIS and IMF as exchange rate variable

| | Dependent Variable: HICP Goods | |
|---|---|---|
| | BIS country-specific NEER | IMF country-specific NEER |
| Constant | 0.001** | 0.001** |
| | (0.000) | (0.000) |
| NEER | -0.042*** | -0.045*** |
| | (0.012) | (0.014) |
| NEER Lag 1 | 0.018** | 0.013 |
| | (0.009) | (0.009) |
| NEER Lag 2 | -0.057*** | -0.056*** |
| | (0.010) | (0.010) |
| NEER Lag 3 | 0.022* | 0.015 |
| | (0.013) | (0.011) |
| NEER Lag 4 | -0.098*** | -0.097*** |
| | (0.020) | (0.020) |
| Cum. Sum of NEER Coefficients | -0.157 | -0.169 |
| F-Statistic NEER Lags | 42.038 | 43.014 |
| Output Gap (+4 Lags) | Yes | Yes |
| Trade-Weighted PPI YoY Change (+4 Lags) | Yes | Yes |
| Country Fixed Effects | Yes | Yes |
| Standard Errors | Clustered | Clustered |
| Observations | 910 | 910 |
| R-Squared | 0.266 | 0.265 |
| | Standard Errors in Parentheses | |
| | ***p<0.01, **p<0.05, *p<0.1 | |

Table 16: Trade weight calculation for the self-constructed euro NEER_XI, 1999-2000

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.011 | 0.003 | 0.014 | 0.014 | 0.020 | 0.024 | 0.025 | 0.022 | 0.034 | 0.012 | 0.013 | 0.031 | 0.008 | 0.011 | 0.041 | 0.068 | 0.194 | 0.171 | 0.283 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.491 | 0.003 | 0.003 | 0.007 | 0.008 | 0.003 | 0.002 | 0.002 | 0.012 | 0.025 | 0.003 | 0.002 | 0.011 | 0.025 | 0.003 | 0.005 | 0.010 | 0.003 | 0.019 | |
| Bulgaria | 0.000 | 0.407 | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 | 0.003 | 0.000 | 0.000 | 0.000 | 0.001 | 0.009 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.003 | |
| Canada | 0.014 | 0.007 | 0.358 | 0.005 | 0.005 | 0.008 | 0.008 | 0.006 | 0.007 | 0.009 | 0.024 | 0.006 | 0.006 | 0.006 | 0.005 | 0.013 | 0.021 | 0.103 | 0.020 | |
| China, P.R.: Hong Kong | 0.010 | 0.004 | 0.003 | 0.343 | 0.014 | 0.005 | 0.008 | 0.009 | 0.001 | 0.005 | 0.005 | 0.001 | 0.002 | 0.045 | 0.006 | 0.017 | 0.023 | 0.005 | 0.016 | |
| China, P.R.: Mainland | 0.060 | 0.034 | 0.024 | 0.373 | 0.813 | 0.049 | 0.038 | 0.063 | 0.042 | 0.051 | 0.032 | 0.045 | 0.020 | 0.086 | 0.034 | 0.044 | 0.036 | 0.046 | 0.068 | |
| Czech Rep. | 0.001 | 0.058 | 0.000 | 0.000 | 0.000 | 0.446 | 0.005 | 0.048 | 0.000 | 0.000 | 0.004 | 0.052 | 0.023 | 0.001 | 0.008 | 0.011 | 0.004 | 0.000 | 0.018 | |
| Denmark | 0.004 | 0.023 | 0.001 | 0.002 | 0.001 | 0.015 | 0.431 | 0.012 | 0.002 | 0.002 | 0.075 | 0.028 | 0.007 | 0.003 | 0.096 | 0.024 | 0.014 | 0.001 | 0.021 | |
| Hungary | 0.001 | 0.030 | 0.000 | 0.000 | 0.000 | 0.038 | 0.003 | 0.368 | 0.000 | 0.000 | 0.003 | 0.024 | 0.058 | 0.003 | 0.005 | 0.012 | 0.004 | 0.001 | 0.018 | |
| Japan | 0.112 | 0.034 | 0.037 | 0.102 | 0.066 | 0.046 | 0.024 | 0.115 | 0.842 | 0.132 | 0.042 | 0.034 | 0.018 | 0.280 | 0.049 | 0.079 | 0.061 | 0.068 | 0.122 | |
| Korea, Rep. of | 0.034 | 0.021 | 0.010 | 0.041 | 0.035 | 0.012 | 0.011 | 0.036 | 0.016 | 0.612 | 0.015 | 0.033 | 0.031 | 0.060 | 0.008 | 0.010 | 0.020 | 0.017 | 0.041 | |
| Norway | 0.001 | 0.003 | 0.008 | 0.001 | 0.001 | 0.018 | 0.079 | 0.004 | 0.001 | 0.002 | 0.425 | 0.015 | 0.003 | 0.002 | 0.110 | 0.006 | 0.029 | 0.002 | 0.020 | |
| Poland, Rep. of | 0.000 | 0.044 | 0.001 | 0.000 | 0.000 | 0.085 | 0.025 | 0.050 | 0.000 | 0.000 | 0.011 | 0.537 | 0.022 | 0.001 | 0.017 | 0.007 | 0.005 | 0.000 | 0.018 | |
| Romania | 0.000 | 0.081 | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 | 0.023 | 0.000 | 0.000 | 0.002 | 0.005 | 0.641 | 0.000 | 0.002 | 0.002 | 0.002 | 0.000 | 0.007 | |
| Singapore | 0.031 | 0.001 | 0.003 | 0.038 | 0.008 | 0.006 | 0.003 | 0.037 | 0.005 | 0.014 | 0.003 | 0.005 | 0.001 | 0.151 | 0.002 | 0.005 | 0.014 | 0.009 | 0.035 | |
| Sweden | 0.013 | 0.036 | 0.004 | 0.002 | 0.004 | 0.035 | 0.169 | 0.028 | 0.002 | 0.002 | 0.169 | 0.049 | 0.020 | 0.008 | 0.404 | 0.040 | 0.029 | 0.004 | 0.040 | |
| Switzerland | 0.009 | 0.043 | 0.003 | 0.009 | 0.002 | 0.041 | 0.017 | 0.034 | 0.003 | 0.005 | 0.013 | 0.023 | 0.017 | 0.027 | 0.021 | 0.356 | 0.033 | 0.005 | 0.054 | |
| United Kingdom | 0.047 | 0.072 | 0.025 | 0.017 | 0.006 | 0.095 | 0.113 | 0.076 | 0.005 | 0.011 | 0.096 | 0.074 | 0.062 | 0.037 | 0.132 | 0.160 | 0.525 | 0.020 | 0.151 | |
| United States | 0.173 | 0.098 | 0.518 | 0.060 | 0.037 | 0.095 | 0.061 | 0.089 | 0.061 | 0.128 | 0.077 | 0.066 | 0.048 | 0.264 | 0.098 | 0.208 | 0.170 | 0.712 | 0.328 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.015 | 0.003 | 0.035 | 0.018 | 0.070 | 0.021 | 0.028 | 0.018 | 0.109 | 0.033 | 0.026 | 0.028 | 0.008 | 0.019 | 0.047 | 0.052 | 0.178 | 0.293 | | 1 |
| **Import weights** | 0.008 | 0.004 | 0.017 | 0.012 | 0.072 | 0.031 | 0.033 | 0.030 | 0.099 | 0.025 | 0.035 | 0.029 | 0.010 | 0.018 | 0.059 | 0.077 | 0.232 | 0.209 | | 1 |
| **Euro area export share** | 0.497 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.503 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.012 | 0.003 | 0.026 | 0.015 | 0.071 | 0.026 | 0.030 | 0.024 | 0.104 | 0.029 | 0.030 | 0.029 | 0.009 | 0.019 | 0.053 | 0.064 | 0.205 | 0.251 | | 1 |

Table 17: Trade weight calculation for the self-constructed euro NEER_XI, 2001-2003

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.011 | 0.004 | 0.015 | 0.014 | 0.029 | 0.028 | 0.024 | 0.023 | 0.031 | 0.013 | 0.012 | 0.032 | 0.010 | 0.011 | 0.037 | 0.062 | 0.191 | 0.168 | 0.286 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.477 | 0.011 | 0.004 | 0.007 | 0.008 | 0.003 | 0.002 | 0.002 | 0.014 | 0.028 | 0.002 | 0.001 | 0.004 | 0.034 | 0.004 | 0.004 | 0.014 | 0.003 | 0.020 | |
| Bulgaria | 0.000 | 0.471 | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 | 0.003 | 0.000 | 0.000 | 0.000 | 0.002 | 0.013 | 0.000 | 0.001 | 0.002 | 0.001 | 0.000 | 0.004 | |
| Canada | 0.013 | 0.007 | 0.379 | 0.005 | 0.005 | 0.006 | 0.007 | 0.006 | 0.007 | 0.009 | 0.025 | 0.005 | 0.006 | 0.008 | 0.005 | 0.012 | 0.024 | 0.106 | 0.019 | |
| China, P.R.: Hong Kong | 0.009 | 0.005 | 0.002 | 0.299 | 0.014 | 0.004 | 0.006 | 0.012 | 0.001 | 0.009 | 0.004 | 0.002 | 0.002 | 0.044 | 0.005 | 0.021 | 0.013 | 0.005 | 0.015 | |
| China, P.R.: Mainland | 0.091 | 0.053 | 0.036 | 0.406 | 0.789 | 0.104 | 0.046 | 0.127 | 0.064 | 0.084 | 0.042 | 0.068 | 0.033 | 0.138 | 0.041 | 0.055 | 0.069 | 0.065 | 0.100 | |
| Czech Rep. | 0.001 | 0.044 | 0.000 | 0.000 | 0.000 | 0.405 | 0.006 | 0.052 | 0.000 | 0.000 | 0.007 | 0.061 | 0.029 | 0.001 | 0.009 | 0.019 | 0.008 | 0.001 | 0.024 | |
| Denmark | 0.005 | 0.020 | 0.002 | 0.002 | 0.001 | 0.015 | 0.405 | 0.014 | 0.002 | 0.002 | 0.086 | 0.029 | 0.007 | 0.003 | 0.122 | 0.027 | 0.018 | 0.002 | 0.023 | |
| Hungary | 0.001 | 0.033 | 0.000 | 0.001 | 0.000 | 0.045 | 0.006 | 0.335 | 0.000 | 0.000 | 0.005 | 0.031 | 0.054 | 0.002 | 0.007 | 0.016 | 0.006 | 0.001 | 0.021 | |
| Japan | 0.114 | 0.032 | 0.033 | 0.107 | 0.077 | 0.049 | 0.017 | 0.097 | 0.815 | 0.148 | 0.037 | 0.034 | 0.017 | 0.235 | 0.038 | 0.071 | 0.056 | 0.060 | 0.113 | |
| Korea, Rep. of | 0.034 | 0.016 | 0.011 | 0.044 | 0.043 | 0.015 | 0.012 | 0.038 | 0.017 | 0.569 | 0.010 | 0.018 | 0.016 | 0.067 | 0.010 | 0.013 | 0.017 | 0.018 | 0.042 | |
| Norway | 0.002 | 0.002 | 0.009 | 0.001 | 0.001 | 0.022 | 0.094 | 0.003 | 0.001 | 0.002 | 0.422 | 0.025 | 0.003 | 0.004 | 0.113 | 0.007 | 0.037 | 0.003 | 0.025 | |
| Poland, Rep. of | 0.001 | 0.038 | 0.001 | 0.000 | 0.000 | 0.094 | 0.028 | 0.058 | 0.000 | 0.000 | 0.014 | 0.516 | 0.030 | 0.000 | 0.028 | 0.011 | 0.008 | 0.001 | 0.024 | |
| Romania | 0.000 | 0.063 | 0.000 | 0.000 | 0.000 | 0.005 | 0.001 | 0.026 | 0.000 | 0.000 | 0.004 | 0.005 | 0.662 | 0.000 | 0.002 | 0.003 | 0.004 | 0.000 | 0.010 | |
| Singapore | 0.031 | 0.003 | 0.002 | 0.044 | 0.010 | 0.012 | 0.007 | 0.025 | 0.005 | 0.017 | 0.004 | 0.007 | 0.003 | 0.111 | 0.002 | 0.007 | 0.012 | 0.007 | 0.033 | |
| Sweden | 0.012 | 0.031 | 0.004 | 0.002 | 0.003 | 0.026 | 0.177 | 0.026 | 0.002 | 0.003 | 0.175 | 0.048 | 0.014 | 0.009 | 0.401 | 0.037 | 0.029 | 0.005 | 0.037 | |
| Switzerland | 0.009 | 0.033 | 0.003 | 0.012 | 0.003 | 0.038 | 0.017 | 0.031 | 0.003 | 0.005 | 0.014 | 0.023 | 0.014 | 0.030 | 0.019 | 0.325 | 0.022 | 0.005 | 0.057 | |
| United Kingdom | 0.042 | 0.069 | 0.023 | 0.015 | 0.005 | 0.075 | 0.113 | 0.064 | 0.006 | 0.012 | 0.082 | 0.070 | 0.052 | 0.037 | 0.118 | 0.159 | 0.483 | 0.021 | 0.144 | |
| United States | 0.158 | 0.067 | 0.488 | 0.055 | 0.039 | 0.078 | 0.055 | 0.082 | 0.060 | 0.112 | 0.066 | 0.055 | 0.041 | 0.274 | 0.075 | 0.212 | 0.179 | 0.697 | 0.290 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.016 | 0.004 | 0.036 | 0.015 | 0.102 | 0.025 | 0.029 | 0.020 | 0.100 | 0.033 | 0.029 | 0.032 | 0.012 | 0.018 | 0.044 | 0.046 | 0.163 | 0.275 | | 1 |
| **Import weights** | 0.008 | 0.005 | 0.015 | 0.009 | 0.098 | 0.041 | 0.035 | 0.036 | 0.081 | 0.026 | 0.043 | 0.038 | 0.014 | 0.015 | 0.055 | 0.078 | 0.218 | 0.183 | | |
| **Euro area export share** | 0.514 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.486 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.012 | 0.004 | 0.026 | 0.012 | 0.100 | 0.033 | 0.032 | 0.028 | 0.091 | 0.030 | 0.036 | 0.035 | 0.013 | 0.017 | 0.049 | 0.062 | 0.190 | 0.231 | | 1 |

Table 18: Trade weight calculation for the self-constructed euro NEER_XI, 2004-2006

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.012 | 0.005 | 0.013 | 0.012 | 0.037 | 0.032 | 0.024 | 0.024 | 0.027 | 0.013 | 0.013 | 0.040 | 0.014 | 0.011 | 0.038 | 0.058 | 0.168 | 0.149 | 0.311 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.485 | 0.010 | 0.004 | 0.006 | 0.016 | 0.001 | 0.003 | 0.001 | 0.020 | 0.028 | 0.002 | 0.001 | 0.002 | 0.029 | 0.005 | 0.003 | 0.014 | 0.003 | 0.020 | |
| Bulgaria | 0.000 | 0.398 | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 | 0.004 | 0.000 | 0.000 | 0.001 | 0.004 | 0.016 | 0.001 | 0.001 | 0.002 | 0.001 | 0.000 | 0.005 | |
| Canada | 0.011 | 0.009 | 0.398 | 0.004 | 0.008 | 0.006 | 0.005 | 0.004 | 0.007 | 0.008 | 0.028 | 0.004 | 0.008 | 0.008 | 0.005 | 0.018 | 0.025 | 0.113 | 0.018 | |
| China, P.R.: Hong Kong | 0.008 | 0.004 | 0.001 | 0.239 | 0.012 | 0.003 | 0.008 | 0.003 | 0.001 | 0.007 | 0.005 | 0.001 | 0.001 | 0.039 | 0.005 | 0.030 | 0.015 | 0.004 | 0.014 | |
| China, P.R.: Mainland | 0.123 | 0.105 | 0.062 | 0.452 | 0.700 | 0.093 | 0.068 | 0.167 | 0.090 | 0.114 | 0.061 | 0.078 | 0.063 | 0.208 | 0.053 | 0.071 | 0.094 | 0.102 | 0.160 | |
| Czech Rep. | 0.001 | 0.042 | 0.001 | 0.001 | 0.000 | 0.366 | 0.011 | 0.068 | 0.000 | 0.001 | 0.008 | 0.089 | 0.038 | 0.001 | 0.013 | 0.024 | 0.010 | 0.001 | 0.028 | |
| Denmark | 0.006 | 0.014 | 0.003 | 0.002 | 0.001 | 0.021 | 0.385 | 0.014 | 0.002 | 0.002 | 0.080 | 0.037 | 0.006 | 0.003 | 0.140 | 0.023 | 0.021 | 0.002 | 0.022 | |
| Hungary | 0.001 | 0.034 | 0.000 | 0.000 | 0.001 | 0.069 | 0.007 | 0.321 | 0.000 | 0.000 | 0.006 | 0.047 | 0.052 | 0.002 | 0.011 | 0.016 | 0.010 | 0.001 | 0.022 | |
| Japan | 0.096 | 0.035 | 0.030 | 0.112 | 0.104 | 0.061 | 0.014 | 0.071 | 0.784 | 0.143 | 0.034 | 0.023 | 0.022 | 0.189 | 0.034 | 0.064 | 0.050 | 0.056 | 0.104 | |
| Korea, Rep. of | 0.032 | 0.022 | 0.012 | 0.046 | 0.077 | 0.013 | 0.016 | 0.043 | 0.021 | 0.573 | 0.013 | 0.026 | 0.022 | 0.084 | 0.014 | 0.015 | 0.017 | 0.019 | 0.050 | |
| Norway | 0.001 | 0.002 | 0.011 | 0.001 | 0.001 | 0.003 | 0.097 | 0.001 | 0.001 | 0.002 | 0.421 | 0.028 | 0.004 | 0.004 | 0.117 | 0.007 | 0.066 | 0.003 | 0.027 | |
| Poland, Rep. of | 0.001 | 0.047 | 0.001 | 0.000 | 0.001 | 0.158 | 0.030 | 0.088 | 0.000 | 0.000 | 0.020 | 0.464 | 0.044 | 0.001 | 0.038 | 0.017 | 0.013 | 0.001 | 0.029 | |
| Romania | 0.000 | 0.097 | 0.000 | 0.000 | 0.000 | 0.010 | 0.001 | 0.050 | 0.000 | 0.000 | 0.004 | 0.010 | 0.598 | 0.001 | 0.002 | 0.004 | 0.004 | 0.000 | 0.011 | |
| Singapore | 0.049 | 0.003 | 0.002 | 0.059 | 0.016 | 0.003 | 0.005 | 0.015 | 0.006 | 0.015 | 0.004 | 0.004 | 0.002 | 0.123 | 0.002 | 0.008 | 0.019 | 0.006 | 0.036 | |
| Sweden | 0.012 | 0.030 | 0.005 | 0.002 | 0.003 | 0.038 | 0.202 | 0.029 | 0.002 | 0.003 | 0.168 | 0.061 | 0.016 | 0.008 | 0.388 | 0.035 | 0.030 | 0.005 | 0.039 | |
| Switzerland | 0.009 | 0.030 | 0.004 | 0.012 | 0.004 | 0.027 | 0.017 | 0.023 | 0.004 | 0.004 | 0.012 | 0.019 | 0.016 | 0.021 | 0.015 | 0.331 | 0.016 | 0.005 | 0.055 | |
| United Kingdom | 0.035 | 0.059 | 0.021 | 0.013 | 0.006 | 0.080 | 0.086 | 0.058 | 0.006 | 0.010 | 0.075 | 0.074 | 0.045 | 0.037 | 0.102 | 0.139 | 0.470 | 0.020 | 0.126 | |
| United States | 0.128 | 0.060 | 0.444 | 0.051 | 0.051 | 0.045 | 0.045 | 0.040 | 0.055 | 0.091 | 0.058 | 0.032 | 0.043 | 0.242 | 0.054 | 0.194 | 0.125 | 0.657 | 0.235 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.017 | 0.004 | 0.035 | 0.014 | 0.140 | 0.030 | 0.030 | 0.023 | 0.092 | 0.039 | 0.034 | 0.042 | 0.015 | 0.020 | 0.047 | 0.044 | 0.145 | 0.227 | | 1 |
| **Import weights** | 0.008 | 0.006 | 0.013 | 0.009 | 0.148 | 0.048 | 0.034 | 0.036 | 0.068 | 0.033 | 0.047 | 0.047 | 0.016 | 0.015 | 0.056 | 0.073 | 0.194 | 0.149 | | |
| **Euro area export share** | 0.502 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.498 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.013 | 0.005 | 0.024 | 0.011 | 0.144 | 0.039 | 0.032 | 0.030 | 0.080 | 0.036 | 0.041 | 0.044 | 0.016 | 0.018 | 0.051 | 0.059 | 0.169 | 0.188 | | 1 |

Table 19: Trade weight calculation for the self-constructed euro NEER_XI, 2007-2009

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.012 | 0.006 | 0.012 | 0.010 | 0.045 | 0.037 | 0.023 | 0.024 | 0.022 | 0.013 | 0.014 | 0.053 | 0.016 | 0.011 | 0.036 | 0.057 | 0.144 | 0.123 | 0.342 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.440 | 0.003 | 0.003 | 0.006 | 0.020 | 0.000 | 0.002 | 0.000 | 0.036 | 0.035 | 0.002 | 0.001 | 0.003 | 0.026 | 0.005 | 0.004 | 0.017 | 0.004 | 0.020 | |
| Bulgaria | 0.000 | 0.309 | 0.000 | 0.000 | 0.000 | 0.003 | 0.001 | 0.004 | 0.000 | 0.000 | 0.001 | 0.004 | 0.033 | 0.002 | 0.001 | 0.002 | 0.001 | 0.000 | 0.005 | |
| Canada | 0.011 | 0.006 | 0.379 | 0.004 | 0.007 | 0.005 | 0.008 | 0.003 | 0.010 | 0.009 | 0.035 | 0.003 | 0.005 | 0.007 | 0.005 | 0.019 | 0.031 | 0.118 | 0.019 | |
| China, P.R.: Hong Kong | 0.007 | 0.009 | 0.001 | 0.198 | 0.007 | 0.020 | 0.005 | 0.002 | 0.001 | 0.004 | 0.003 | 0.001 | 0.001 | 0.022 | 0.004 | 0.024 | 0.017 | 0.002 | 0.012 | |
| China, P.R.: Mainland | 0.163 | 0.090 | 0.083 | 0.492 | 0.749 | 0.136 | 0.091 | 0.197 | 0.125 | 0.149 | 0.075 | 0.107 | 0.075 | 0.205 | 0.066 | 0.093 | 0.117 | 0.134 | 0.213 | |
| Czech Rep. | 0.001 | 0.072 | 0.001 | 0.001 | 0.001 | 0.326 | 0.016 | 0.089 | 0.000 | 0.001 | 0.010 | 0.094 | 0.045 | 0.001 | 0.019 | 0.033 | 0.015 | 0.001 | 0.033 | |
| Denmark | 0.005 | 0.016 | 0.003 | 0.002 | 0.001 | 0.020 | 0.325 | 0.017 | 0.002 | 0.002 | 0.075 | 0.034 | 0.008 | 0.005 | 0.139 | 0.020 | 0.017 | 0.002 | 0.019 | |
| Hungary | 0.002 | 0.096 | 0.001 | 0.000 | 0.001 | 0.072 | 0.012 | 0.271 | 0.001 | 0.001 | 0.006 | 0.046 | 0.140 | 0.002 | 0.011 | 0.020 | 0.011 | 0.001 | 0.022 | |
| Japan | 0.091 | 0.015 | 0.030 | 0.101 | 0.082 | 0.053 | 0.010 | 0.063 | 0.709 | 0.128 | 0.026 | 0.021 | 0.010 | 0.149 | 0.028 | 0.071 | 0.037 | 0.052 | 0.093 | |
| Korea, Rep. of | 0.031 | 0.010 | 0.012 | 0.042 | 0.063 | 0.017 | 0.008 | 0.053 | 0.025 | 0.554 | 0.015 | 0.047 | 0.019 | 0.101 | 0.012 | 0.012 | 0.013 | 0.019 | 0.052 | |
| Norway | 0.002 | 0.002 | 0.011 | 0.001 | 0.001 | 0.003 | 0.102 | 0.001 | 0.002 | 0.005 | 0.412 | 0.022 | 0.003 | 0.009 | 0.129 | 0.006 | 0.077 | 0.003 | 0.026 | |
| Poland, Rep. of | 0.002 | 0.067 | 0.002 | 0.000 | 0.001 | 0.172 | 0.041 | 0.099 | 0.000 | 0.001 | 0.027 | 0.435 | 0.064 | 0.001 | 0.047 | 0.022 | 0.019 | 0.001 | 0.035 | |
| Romania | 0.000 | 0.167 | 0.000 | 0.000 | 0.000 | 0.010 | 0.001 | 0.055 | 0.000 | 0.000 | 0.006 | 0.009 | 0.501 | 0.001 | 0.002 | 0.004 | 0.004 | 0.000 | 0.011 | |
| Singapore | 0.061 | 0.001 | 0.003 | 0.070 | 0.011 | 0.007 | 0.011 | 0.012 | 0.007 | 0.018 | 0.004 | 0.003 | 0.001 | 0.190 | 0.001 | 0.010 | 0.014 | 0.007 | 0.034 | |
| Sweden | 0.012 | 0.024 | 0.004 | 0.001 | 0.003 | 0.026 | 0.219 | 0.026 | 0.002 | 0.003 | 0.160 | 0.056 | 0.015 | 0.007 | 0.371 | 0.029 | 0.027 | 0.005 | 0.034 | |
| Switzerland | 0.011 | 0.033 | 0.006 | 0.015 | 0.004 | 0.025 | 0.015 | 0.019 | 0.006 | 0.004 | 0.012 | 0.015 | 0.014 | 0.016 | 0.013 | 0.291 | 0.029 | 0.007 | 0.053 | |
| United Kingdom | 0.039 | 0.046 | 0.023 | 0.013 | 0.005 | 0.072 | 0.083 | 0.053 | 0.007 | 0.008 | 0.070 | 0.069 | 0.037 | 0.031 | 0.098 | 0.137 | 0.434 | 0.022 | 0.102 | |
| United States | 0.121 | 0.032 | 0.438 | 0.054 | 0.045 | 0.032 | 0.050 | 0.036 | 0.067 | 0.080 | 0.060 | 0.032 | 0.025 | 0.224 | 0.050 | 0.202 | 0.117 | 0.623 | 0.216 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.018 | 0.005 | 0.033 | 0.012 | 0.183 | 0.037 | 0.027 | 0.026 | 0.079 | 0.041 | 0.035 | 0.052 | 0.016 | 0.021 | 0.044 | 0.044 | 0.125 | 0.201 | | 1 |
| **Import weights** | 0.007 | 0.006 | 0.014 | 0.007 | 0.184 | 0.061 | 0.032 | 0.038 | 0.057 | 0.030 | 0.049 | 0.060 | 0.016 | 0.012 | 0.052 | 0.073 | 0.165 | 0.138 | | 1 |
| **Euro area export share** | 0.497 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.503 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.013 | 0.006 | 0.024 | 0.009 | 0.183 | 0.049 | 0.029 | 0.032 | 0.068 | 0.035 | 0.042 | 0.056 | 0.016 | 0.016 | 0.048 | 0.059 | 0.145 | 0.169 | | 1 |

Table 20: Trade weight calculation for the self-constructed euro NEER_XI, 2010-2012

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.013 | 0.005 | 0.012 | 0.013 | 0.064 | 0.036 | 0.019 | 0.022 | 0.023 | 0.015 | 0.012 | 0.051 | 0.015 | 0.012 | 0.034 | 0.062 | 0.123 | 0.117 | 0.350 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.426 | 0.001 | 0.004 | 0.006 | 0.026 | 0.000 | 0.003 | 0.000 | 0.038 | 0.046 | 0.002 | 0.002 | 0.000 | 0.021 | 0.004 | 0.008 | 0.017 | 0.003 | 0.020 | |
| Bulgaria | 0.000 | 0.310 | 0.000 | 0.000 | 0.000 | 0.003 | 0.002 | 0.006 | 0.000 | 0.000 | 0.001 | 0.005 | 0.045 | 0.001 | 0.001 | 0.002 | 0.001 | 0.000 | 0.006 | |
| Canada | 0.009 | 0.004 | 0.368 | 0.004 | 0.007 | 0.002 | 0.006 | 0.004 | 0.009 | 0.011 | 0.040 | 0.004 | 0.003 | 0.006 | 0.005 | 0.013 | 0.040 | 0.110 | 0.018 | |
| China, P.R.: Hong Kong | 0.005 | 0.007 | 0.001 | 0.110 | 0.005 | 0.022 | 0.003 | 0.002 | 0.001 | 0.004 | 0.003 | 0.001 | 0.000 | 0.016 | 0.004 | 0.030 | 0.013 | 0.002 | 0.011 | |
| China, P.R.: Mainland | 0.193 | 0.089 | 0.096 | 0.544 | 0.768 | 0.170 | 0.109 | 0.209 | 0.125 | 0.159 | 0.105 | 0.122 | 0.070 | 0.190 | 0.075 | 0.110 | 0.125 | 0.145 | 0.250 | |
| Czech Rep. | 0.002 | 0.058 | 0.001 | 0.001 | 0.001 | 0.322 | 0.019 | 0.083 | 0.000 | 0.001 | 0.012 | 0.100 | 0.037 | 0.001 | 0.019 | 0.031 | 0.016 | 0.001 | 0.033 | |
| Denmark | 0.005 | 0.013 | 0.003 | 0.003 | 0.001 | 0.015 | 0.318 | 0.016 | 0.002 | 0.001 | 0.073 | 0.033 | 0.008 | 0.003 | 0.128 | 0.013 | 0.020 | 0.002 | 0.015 | |
| Hungary | 0.002 | 0.096 | 0.001 | 0.001 | 0.001 | 0.060 | 0.012 | 0.261 | 0.001 | 0.001 | 0.005 | 0.044 | 0.135 | 0.004 | 0.010 | 0.013 | 0.011 | 0.001 | 0.020 | |
| Japan | 0.085 | 0.009 | 0.028 | 0.101 | 0.066 | 0.030 | 0.008 | 0.041 | 0.726 | 0.131 | 0.026 | 0.017 | 0.007 | 0.127 | 0.023 | 0.061 | 0.032 | 0.048 | 0.086 | |
| Korea, Rep. of | 0.037 | 0.013 | 0.013 | 0.047 | 0.056 | 0.033 | 0.007 | 0.047 | 0.026 | 0.515 | 0.027 | 0.042 | 0.013 | 0.112 | 0.014 | 0.009 | 0.009 | 0.020 | 0.056 | |
| Norway | 0.002 | 0.001 | 0.007 | 0.001 | 0.001 | 0.001 | 0.099 | 0.001 | 0.002 | 0.008 | 0.356 | 0.027 | 0.003 | 0.006 | 0.130 | 0.006 | 0.086 | 0.003 | 0.022 | |
| Poland, Rep. of | 0.002 | 0.065 | 0.002 | 0.001 | 0.001 | 0.175 | 0.048 | 0.118 | 0.001 | 0.001 | 0.032 | 0.410 | 0.061 | 0.001 | 0.044 | 0.021 | 0.026 | 0.001 | 0.035 | |
| Romania | 0.000 | 0.215 | 0.001 | 0.000 | 0.000 | 0.014 | 0.003 | 0.071 | 0.000 | 0.001 | 0.006 | 0.014 | 0.537 | 0.001 | 0.004 | 0.006 | 0.005 | 0.000 | 0.012 | |
| Singapore | 0.061 | 0.002 | 0.003 | 0.079 | 0.010 | 0.016 | 0.005 | 0.011 | 0.006 | 0.018 | 0.007 | 0.006 | 0.001 | 0.254 | 0.001 | 0.017 | 0.011 | 0.007 | 0.035 | |
| Sweden | 0.011 | 0.018 | 0.004 | 0.001 | 0.002 | 0.022 | 0.206 | 0.025 | 0.002 | 0.003 | 0.160 | 0.056 | 0.009 | 0.007 | 0.383 | 0.023 | 0.029 | 0.004 | 0.029 | |
| Switzerland | 0.012 | 0.026 | 0.006 | 0.023 | 0.007 | 0.021 | 0.015 | 0.015 | 0.005 | 0.005 | 0.014 | 0.012 | 0.013 | 0.023 | 0.012 | 0.301 | 0.037 | 0.008 | 0.055 | |
| United Kingdom | 0.030 | 0.048 | 0.020 | 0.015 | 0.005 | 0.060 | 0.092 | 0.048 | 0.005 | 0.009 | 0.069 | 0.067 | 0.036 | 0.032 | 0.093 | 0.130 | 0.400 | 0.019 | 0.086 | |
| United States | 0.119 | 0.023 | 0.442 | 0.065 | 0.042 | 0.032 | 0.044 | 0.042 | 0.053 | 0.086 | 0.064 | 0.039 | 0.019 | 0.195 | 0.049 | 0.207 | 0.121 | 0.625 | 0.213 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.020 | 0.005 | 0.032 | 0.011 | 0.218 | 0.036 | 0.023 | 0.023 | 0.075 | 0.044 | 0.032 | 0.051 | 0.017 | 0.023 | 0.040 | 0.048 | 0.105 | 0.199 | | 1 |
| **Import weights** | 0.007 | 0.008 | 0.014 | 0.006 | 0.202 | 0.069 | 0.028 | 0.037 | 0.048 | 0.025 | 0.045 | 0.067 | 0.019 | 0.014 | 0.049 | 0.075 | 0.152 | 0.135 | | 1 |
| **Euro area export share** | 0.503 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.497 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.014 | 0.007 | 0.023 | 0.008 | 0.210 | 0.052 | 0.025 | 0.030 | 0.062 | 0.035 | 0.038 | 0.059 | 0.018 | 0.018 | 0.044 | 0.061 | 0.128 | 0.167 | | 1 |

Table 21: Trade weight calculation for the self-constructed euro NEER_XI, 2013-2015

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.012 | 0.006 | 0.013 | 0.012 | 0.065 | 0.035 | 0.019 | 0.023 | 0.022 | 0.018 | 0.012 | 0.053 | 0.016 | 0.011 | 0.032 | 0.057 | 0.129 | 0.126 | 0.341 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.396 | 0.011 | 0.003 | 0.007 | 0.026 | 0.001 | 0.002 | 0.001 | 0.043 | 0.041 | 0.002 | 0.003 | 0.001 | 0.022 | 0.003 | 0.005 | 0.009 | 0.003 | 0.017 | |
| Bulgaria | 0.000 | 0.257 | 0.000 | 0.000 | 0.000 | 0.005 | 0.002 | 0.010 | 0.000 | 0.000 | 0.001 | 0.006 | 0.048 | 0.003 | 0.001 | 0.002 | 0.001 | 0.000 | 0.006 | |
| Canada | 0.009 | 0.003 | 0.357 | 0.005 | 0.007 | 0.002 | 0.006 | 0.003 | 0.010 | 0.010 | 0.028 | 0.003 | 0.002 | 0.006 | 0.004 | 0.014 | 0.036 | 0.109 | 0.017 | |
| China, P.R.: Hong Kong | 0.005 | 0.008 | 0.000 | 0.064 | 0.004 | 0.025 | 0.002 | 0.002 | 0.002 | 0.004 | 0.002 | 0.002 | 0.000 | 0.016 | 0.004 | 0.020 | 0.008 | 0.002 | 0.011 | |
| China, P.R.: Mainland | 0.227 | 0.101 | 0.101 | 0.591 | 0.779 | 0.162 | 0.110 | 0.172 | 0.168 | 0.185 | 0.117 | 0.149 | 0.067 | 0.239 | 0.090 | 0.098 | 0.152 | 0.155 | 0.275 | |
| Czech Rep. | 0.003 | 0.066 | 0.001 | 0.001 | 0.001 | 0.284 | 0.025 | 0.120 | 0.001 | 0.001 | 0.013 | 0.095 | 0.046 | 0.002 | 0.022 | 0.019 | 0.019 | 0.001 | 0.033 | |
| Denmark | 0.005 | 0.013 | 0.002 | 0.003 | 0.001 | 0.016 | 0.317 | 0.018 | 0.002 | 0.002 | 0.073 | 0.032 | 0.011 | 0.003 | 0.127 | 0.006 | 0.018 | 0.002 | 0.015 | |
| Hungary | 0.002 | 0.103 | 0.001 | 0.001 | 0.001 | 0.065 | 0.013 | 0.241 | 0.001 | 0.001 | 0.005 | 0.041 | 0.133 | 0.002 | 0.011 | 0.009 | 0.010 | 0.002 | 0.020 | |
| Japan | 0.080 | 0.009 | 0.024 | 0.084 | 0.048 | 0.021 | 0.006 | 0.033 | 0.647 | 0.112 | 0.027 | 0.015 | 0.007 | 0.108 | 0.018 | 0.029 | 0.026 | 0.045 | 0.073 | |
| Korea, Rep. of | 0.052 | 0.010 | 0.013 | 0.051 | 0.057 | 0.037 | 0.028 | 0.032 | 0.031 | 0.498 | 0.000 | 0.034 | 0.013 | 0.117 | 0.009 | 0.005 | 0.015 | 0.023 | 0.056 | |
| Norway | 0.002 | 0.002 | 0.004 | 0.001 | 0.001 | 0.001 | 0.106 | 0.001 | 0.002 | 0.006 | 0.359 | 0.025 | 0.003 | 0.008 | 0.132 | 0.003 | 0.067 | 0.002 | 0.019 | |
| Poland, Rep. of | 0.003 | 0.088 | 0.003 | 0.001 | 0.001 | 0.208 | 0.053 | 0.139 | 0.001 | 0.002 | 0.039 | 0.395 | 0.077 | 0.002 | 0.054 | 0.014 | 0.032 | 0.002 | 0.038 | |
| Romania | 0.000 | 0.207 | 0.001 | 0.000 | 0.000 | 0.022 | 0.004 | 0.083 | 0.000 | 0.001 | 0.009 | 0.016 | 0.511 | 0.000 | 0.006 | 0.005 | 0.006 | 0.001 | 0.013 | |
| Singapore | 0.051 | 0.002 | 0.002 | 0.077 | 0.009 | 0.010 | 0.003 | 0.007 | 0.007 | 0.021 | 0.008 | 0.009 | 0.001 | 0.204 | 0.001 | 0.013 | 0.007 | 0.006 | 0.034 | |
| Sweden | 0.009 | 0.018 | 0.003 | 0.001 | 0.002 | 0.022 | 0.195 | 0.026 | 0.002 | 0.004 | 0.152 | 0.057 | 0.010 | 0.006 | 0.364 | 0.014 | 0.030 | 0.003 | 0.026 | |
| Switzerland | 0.013 | 0.022 | 0.007 | 0.030 | 0.011 | 0.020 | 0.012 | 0.014 | 0.007 | 0.006 | 0.016 | 0.011 | 0.013 | 0.022 | 0.012 | 0.230 | 0.029 | 0.010 | 0.052 | |
| United Kingdom | 0.028 | 0.051 | 0.015 | 0.018 | 0.006 | 0.061 | 0.078 | 0.049 | 0.006 | 0.014 | 0.078 | 0.066 | 0.039 | 0.036 | 0.097 | 0.345 | 0.402 | 0.018 | 0.078 | |
| United States | 0.117 | 0.028 | 0.463 | 0.068 | 0.046 | 0.036 | 0.039 | 0.049 | 0.069 | 0.093 | 0.073 | 0.041 | 0.019 | 0.202 | 0.044 | 0.168 | 0.135 | 0.615 | 0.217 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.017 | 0.005 | 0.032 | 0.009 | 0.235 | 0.035 | 0.022 | 0.022 | 0.062 | 0.045 | 0.028 | 0.054 | 0.019 | 0.020 | 0.036 | 0.040 | 0.116 | 0.203 | | 1 |
| **Import weights** | 0.006 | 0.009 | 0.013 | 0.006 | 0.198 | 0.072 | 0.027 | 0.040 | 0.039 | 0.023 | 0.041 | 0.077 | 0.022 | 0.013 | 0.048 | 0.076 | 0.143 | 0.145 | | 1 |
| **Euro area export share** | 0.526 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.474 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.011 | 0.007 | 0.023 | 0.008 | 0.218 | 0.053 | 0.025 | 0.031 | 0.051 | 0.034 | 0.034 | 0.065 | 0.021 | 0.016 | 0.042 | 0.057 | 0.129 | 0.176 | | 1 |

Table 22: Trade weight calculation for the self-constructed euro NEER_XI, 2016-2022

| | Australia | Bulgaria | Canada | China, P.R.: Hong Kong | China, P.R.: Mainland | Czech Rep. | Denmark | Hungary | Japan | Korea, Rep. of | Norway | Poland, Rep. of | Romania | Singapore | Sweden | Switzerland | United Kingdom | United States | Rest of World | **Sum** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Euro area exports** | 0.012 | 0.006 | 0.013 | 0.012 | 0.072 | 0.039 | 0.019 | 0.025 | 0.022 | 0.018 | 0.011 | 0.058 | 0.019 | 0.012 | 0.033 | 0.057 | 0.126 | 0.137 | 0.309 | 1 |
| **Supply structure matrix** | | | | | | | | | | | | | | | | | | | | |
| Australia | 0.375 | 0.003 | 0.003 | 0.016 | 0.023 | 0.001 | 0.002 | 0.001 | 0.034 | 0.034 | 0.002 | 0.004 | 0.001 | 0.023 | 0.004 | 0.010 | 0.013 | 0.003 | 0.017 | |
| Bulgaria | 0.000 | 0.294 | 0.000 | 0.000 | 0.000 | 0.007 | 0.002 | 0.011 | 0.000 | 0.000 | 0.001 | 0.006 | 0.050 | 0.001 | 0.002 | 0.003 | 0.001 | 0.000 | 0.006 | |
| Canada | 0.008 | 0.005 | 0.321 | 0.004 | 0.006 | 0.003 | 0.005 | 0.002 | 0.009 | 0.009 | 0.025 | 0.003 | 0.002 | 0.007 | 0.005 | 0.014 | 0.034 | 0.095 | 0.016 | |
| China, P.R.: Hong Kong | 0.004 | 0.009 | 0.001 | 0.055 | 0.003 | 0.022 | 0.002 | 0.001 | 0.002 | 0.003 | 0.002 | 0.000 | 0.000 | 0.019 | 0.004 | 0.064 | 0.013 | 0.002 | 0.012 | |
| China, P.R.: Mainland | 0.260 | 0.105 | 0.115 | 0.575 | 0.811 | 0.172 | 0.116 | 0.164 | 0.147 | 0.180 | 0.128 | 0.185 | 0.090 | 0.245 | 0.094 | 0.121 | 0.144 | 0.160 | 0.298 | |
| Czech Rep. | 0.003 | 0.061 | 0.001 | 0.000 | 0.001 | 0.288 | 0.028 | 0.130 | 0.001 | 0.001 | 0.014 | 0.095 | 0.050 | 0.002 | 0.026 | 0.022 | 0.017 | 0.001 | 0.036 | |
| Denmark | 0.005 | 0.012 | 0.002 | 0.001 | 0.001 | 0.014 | 0.317 | 0.017 | 0.002 | 0.001 | 0.070 | 0.030 | 0.007 | 0.002 | 0.125 | 0.007 | 0.016 | 0.003 | 0.014 | |
| Hungary | 0.002 | 0.096 | 0.001 | 0.001 | 0.001 | 0.061 | 0.014 | 0.233 | 0.001 | 0.001 | 0.005 | 0.044 | 0.126 | 0.002 | 0.016 | 0.010 | 0.009 | 0.002 | 0.021 | |
| Japan | 0.083 | 0.010 | 0.027 | 0.075 | 0.042 | 0.022 | 0.008 | 0.036 | 0.685 | 0.097 | 0.026 | 0.014 | 0.008 | 0.113 | 0.017 | 0.039 | 0.030 | 0.044 | 0.070 | |
| Korea, Rep. of | 0.048 | 0.011 | 0.016 | 0.068 | 0.046 | 0.038 | 0.016 | 0.040 | 0.025 | 0.539 | 0.039 | 0.031 | 0.010 | 0.086 | 0.011 | 0.007 | 0.013 | 0.023 | 0.058 | |
| Norway | 0.002 | 0.003 | 0.003 | 0.000 | 0.001 | 0.001 | 0.099 | 0.001 | 0.002 | 0.003 | 0.305 | 0.015 | 0.001 | 0.004 | 0.136 | 0.004 | 0.053 | 0.002 | 0.014 | |
| Poland, Rep. of | 0.004 | 0.097 | 0.003 | 0.001 | 0.001 | 0.206 | 0.065 | 0.147 | 0.001 | 0.001 | 0.044 | 0.371 | 0.094 | 0.003 | 0.066 | 0.020 | 0.032 | 0.002 | 0.042 | |
| Romania | 0.001 | 0.186 | 0.001 | 0.000 | 0.000 | 0.027 | 0.005 | 0.078 | 0.001 | 0.001 | 0.006 | 0.019 | 0.482 | 0.001 | 0.005 | 0.006 | 0.006 | 0.001 | 0.015 | |
| Singapore | 0.035 | 0.003 | 0.002 | 0.082 | 0.008 | 0.006 | 0.009 | 0.007 | 0.008 | 0.014 | 0.006 | 0.004 | 0.001 | 0.215 | 0.002 | 0.026 | 0.006 | 0.007 | 0.031 | |
| Sweden | 0.009 | 0.017 | 0.004 | 0.001 | 0.002 | 0.019 | 0.193 | 0.023 | 0.002 | 0.003 | 0.150 | 0.056 | 0.010 | 0.006 | 0.344 | 0.015 | 0.021 | 0.003 | 0.024 | |
| Switzerland | 0.013 | 0.020 | 0.007 | 0.036 | 0.009 | 0.016 | 0.012 | 0.014 | 0.007 | 0.005 | 0.015 | 0.011 | 0.010 | 0.042 | 0.012 | 0.241 | 0.040 | 0.012 | 0.048 | |
| United Kingdom | 0.028 | 0.047 | 0.014 | 0.018 | 0.006 | 0.058 | 0.063 | 0.051 | 0.006 | 0.011 | 0.074 | 0.064 | 0.038 | 0.034 | 0.087 | 0.193 | 0.403 | 0.018 | 0.071 | |
| United States | 0.119 | 0.022 | 0.478 | 0.066 | 0.038 | 0.038 | 0.044 | 0.044 | 0.067 | 0.094 | 0.088 | 0.046 | 0.020 | 0.194 | 0.045 | 0.198 | 0.147 | 0.623 | 0.208 | |
| **Sum** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| **Double export weights** | 0.016 | 0.006 | 0.029 | 0.012 | 0.249 | 0.038 | 0.021 | 0.023 | 0.061 | 0.045 | 0.022 | 0.058 | 0.021 | 0.019 | 0.033 | 0.040 | 0.101 | 0.205 | | 1 |
| **Import weights** | 0.005 | 0.010 | 0.013 | 0.004 | 0.209 | 0.078 | 0.026 | 0.042 | 0.039 | 0.025 | 0.028 | 0.087 | 0.027 | 0.013 | 0.046 | 0.074 | 0.129 | 0.147 | | 1 |
| **Euro area export share** | 0.529 | | | | | | | | | | | | | | | | | | | |
| **Euro area import share** | 0.471 | | | | | | | | | | | | | | | | | | | |
| **Overall weights** | 0.011 | 0.008 | 0.022 | 0.008 | 0.230 | 0.057 | 0.023 | 0.032 | 0.051 | 0.036 | 0.025 | 0.072 | 0.023 | 0.016 | 0.039 | 0.056 | 0.114 | 0.178 | | 1 |

# 3. A microscopic analysis of UK retail price fluctuations following the Brexit vote with scanner data

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**Abstract**

The Brexit vote on June 23, 2016 initiated the United Kingdom's departure from the European Union and was accompanied by a sharp depreciation of the Pound sterling. This paper examines retail price dynamics around the time of the referendum from a microscopic perspective, using an exceptionally detailed scanner dataset of 'fast-moving consumer goods' (FMCG). I find that prices exhibited a slight downward trend prior to the referendum, but started to move sharply upward following the referendum. These price dynamics are obtained by incorporating the extensive margin, i.e. price changes of newly introduced and re-appearing products, which command a considerable expenditure share and prove to have inflationary effects. Furthermore, I show that imported products did not become significantly pricier than their domestically produced close substitutes in the aftermath of the Brexit referendum. Moreover, I provide empirical evidence that the Brexit vote-induced depreciation shock on the Pound sterling had profound welfare and distributional implications. Although the inflationary impact was felt throughout all social classes, the magnitude of the impact notably varied between them. Specifically, the 'Upper Middle Class' experienced the steepest increase of prices (8.7 percent between June 2016 and December 2017), and the 'Working Class' the least (4.7 percent within the same time frame). This suggests that the 'Working Class' either selected products with minimal price increases or adjusted their spending habits to circumvent some of the observed price increases. However, even with strategic spending shifts, they could not entirely escape the inflationary impact. Given their tighter budgets, this implies that the 'Working Class' – notably major supporters of the 'Leave' campaign – were among the most impacted by the subsequent price hikes. Most alarmingly, however, is the finding that households at the lowest level of subsistence experienced high inflation (6.6 percent between June 2016 and December 2017) and thus suffered effectively the most. A potential explanation for this observation is that consumption of the lowest income households may predominantly be targeted at the most affordable variants of essential products, which implies that they have limited opportunities to switch to alternative products, even if those variants experience price increases.

**Keywords**

Brexit, Exchange Rate Pass-through, Micro-Level Inflation Analysis, Scanner Data

**JEL-Codes**

E31 · D31 · F15 · F31 · F41

## 3.1. Introduction

This study examines the micro-level impacts of the Brexit vote-induced depreciation shock on the Pound sterling ('Brexit-vote depreciation'), specifically its effects on retail prices and living costs across different social classes. The analysis leverages a unique scanner dataset, providing detailed transaction information on household purchases of 'fast-moving consumer goods' (FMCG), which include products typically available in supermarkets, such as food, drinks, alcohol, personal care, household cleaning, cosmetics, etc. The richness of this dataset enables a deeper understanding of the speed and mechanisms of price adjustments following the Brexit-vote depreciation, further elaborating the findings presented by Breinlich et al. (2021).

The study uses the Brexit vote as the primary point of investigation, but its implications reach far beyond this singular event. At the heart of this research lies the microscopic examination of inflation dynamics, an area that, owing to extensive data requirements, has often been overlooked. My ambition is to provide a fresh micro perspective on different inflation channels. Rather than simply differentiating between static and dynamic product baskets and expenditure weights, I examine the inflationary effects of product introductions and re-appearances and gauge their economic significance. The potential differences in price dynamics of imported products and their domestically produced close substitutes is another key point of the analysis. Furthermore, I delve into the distributional effects of inflationary episodes, extending the scope of this study to understand not just how inflation occurs, but also who it impacts the most.

The Brexit vote is a fitting case study for at least two key reasons. First, as a defining moment in recent European history, it is essential to understand its economic consequences. Second, existing literature suggests that the Brexit vote has had inflationary effects (see Breinlich et al., 2021, but also Gerstein et al., 2019 and Dhingra & Sampson, 2022). Taking these inflationary effects as given, I seek to dissect the specific mechanisms and patterns of inflation that emerged around the time of the referendum.

This study also advocates the use of scanner data in constructing official inflation figures. Traditional methods for collecting price data and computing price indices often fall short in capturing the more complex yet significant facets of price dynamics explored in this paper. For example, as highlighted by Dubois & Griffith & O'Connell (2022), traditional data underlying Consumer Price Indices possess inherent limitations for capturing inflation experienced both at the aggregate level and across different households.[1] First, the data collection on expenditure shares predominantly covers product categories (e.g., meat or vegetables), assigning uniform weight to all products within a respective category. Second, given that price data collection involves a significant component of in-person acquisition, the range of products that are incorporated into the calculation of the price index is restricted. Third, official statistics tend to record a single price for each product in the basket during each time period, thus failing to document the fluctuations in prices that consumers might encounter for these products. As DellaVigna & Gentzkow (2019) demonstrate, this can lead to imprecise inflation assessment because a single retail chain can exhibit substantial weekly price

[1] Most statistical authorities are primarily concerned about inflation experienced by the 'representative' consumer, potentially reasoning the neglect of finer details that emerge from a more granular data analysis.

variations for a given product, a phenomenon pervasive across multiple products and chains. Scanner data, on the other hand, with its high granularity and comprehensive coverage, offers a more solid ground for capturing these complexities. More generally, I believe that scanner data is very useful to study a range of questions in international and monetary economics (such as the measurement of inflation both at aggregate and disaggregate levels, or drivers of price fluctuations), as it offers detailed insights into transaction prices and quantities of specific products, segmented across households, retailers and time.

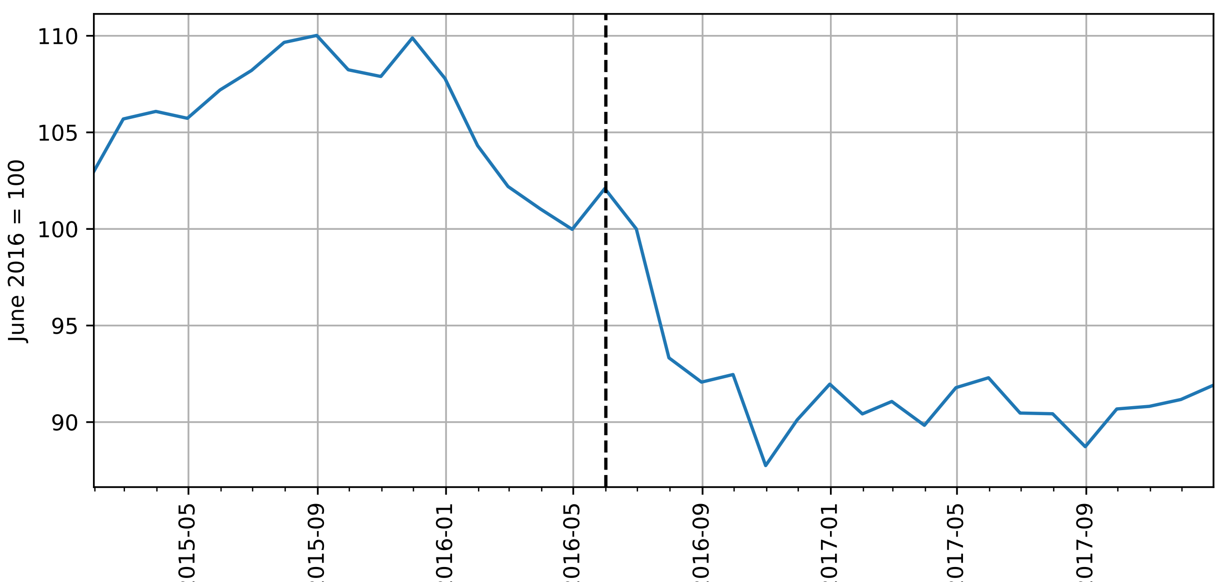
The remainder of this paper is structured as follows: In Section 3.2., I revisit the relationship of the Brexit vote and consumer prices with the scanner data set. The goal is not to make causal inferences as in Breinlich et al. (2021), Gerstein et al. (2019) and Dhingra & Sampson (2022), but to highlight several key micro features in the price evolution around the time of the referendum. These are derived from three methodologies employed in calculating price indices: Static basket with static weights, static basket with dynamic weights, and dynamic basket with dynamic weights. In Section 3.3., I shift the focus towards an aspect of price indices that traditional methodologies often fail to capture: Extensive margin adjustments, involving the introduction of 'successor products' into the market. These changes, although significant, tend to be disregarded in standard price indices given the impracticality of computing price relatives for newly introduced products due to the absence of their pricing data in the preceding period. More specifically, I distinguish between three distinct types of 'successions' and demonstrate that their combined effect on the price evolution is both inflationary and economically significant. Furthermore, I highlight that the Brexit vote intensified the inflationary impact of these successions. These inflationary effects become even more pronounced when I move from the 'succession bias' to the broader scope of 'extensive margin bias'. In Section 3.4., I contrast the price dynamics of foreign/imported products to those of domestically produced products ('domestic products'). I show that foreign products have not become significantly pricier than their domestic counterparts, neither on an aggregate nor on a more granular level. This finding questions a prevailing macroeconomic belief that foreign products are significantly more affected following large currency depreciations than domestically produced products – at least on the retail level. I argue that a combination of factors, including the dependence of domestic products on imported materials and the complex pricing strategies of distributors or retailers, may potentially explain this empirical finding. In Section 3.5., I focus on welfare and distributional effects, specifically evaluating the inflationary impacts across various social classes. My findings indicate that the inflationary impact was felt throughout all social classes. Moreover, I find that the working class faced relatively less inflation than the middle class, possibly due to 'expenditure switching'. However, working class households could not fully mitigate the inflationary effects. When juxtaposed with income data, it becomes evident that, in real terms, the working class was hardly hit by the post-referendum inflation. Most alarmingly, however, is the finding that households at the lowest level of subsistence experienced relatively high inflation and thus suffered effectively the most from the Brexit-vote depreciation. Finally, Section 3.6. offers a summary, some conclusions and open questions emerging from this analysis.

## 3.2. Revisiting the relationship of the Brexit vote and consumer prices with scanner data

In the initial section of this study, I aim to corroborate the findings of Breinlich et al. (2021), Gerstein et al. (2019) and Dhingra & Sampson (2022), which link the Brexit-vote depreciation (see Figure 1) to a significant surge in consumer prices (see Figure 2). This general price surge was one of the most immediate effects of the Brexit vote, felt throughout the UK.

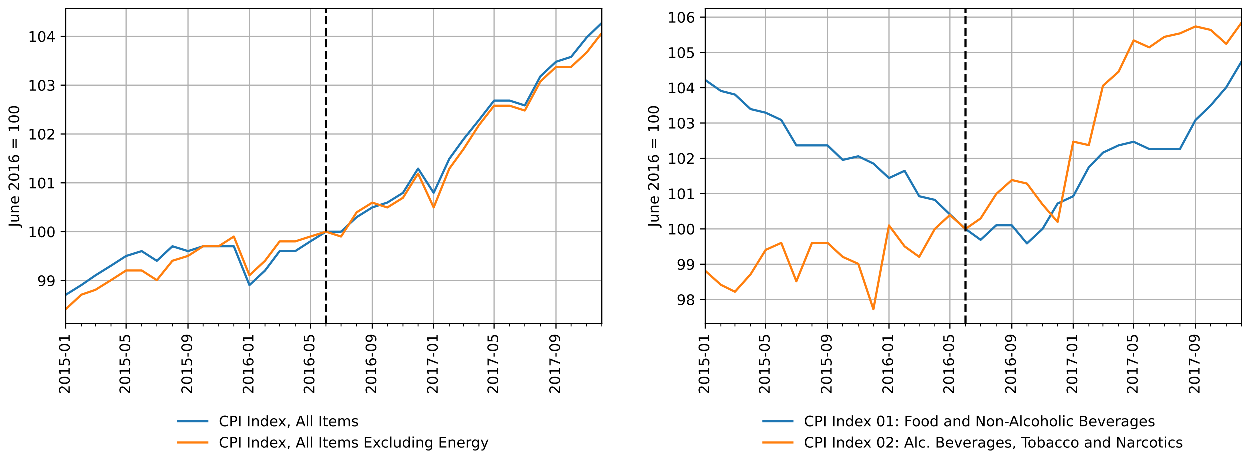
In March 2017, Ben Broadbent, the Deputy Governor for Monetary Policy at the Bank of England, articulated that the decision to exit the EU precipitated a considerable depreciation in the value of the Pound sterling. He noted that the "*vote to leave the EU led to a big drop in sterling's exchange rate. [..] Sterling's more recent decline was clearly prompted by the referendum result. It also seems likely that the foreign exchange market has decided the consequences are negative. The most plausible explanation for the depreciation is that, in the eyes of the market, leaving the EU will make exporting harder and more costly. To help compensate the currency needs to be cheaper*" (Broadbent, 2017, p.2). It is evident that the Pound sterling had been experiencing a decline even before the referendum took place. Mr. Broadbent attributes this phenomenon to the anticipatory reactions of the market to the fluctuating probabilities of a 'Leave' vote in the period leading up to the referendum. Consequently, both depreciation periods of the Pound sterling can be attributed to the (anticipated) outcomes of the Brexit referendum, justifying the use of the term 'Brexit-vote depreciation' for the Pound sterling's valuation change throughout 2016 in this paper.

Figure 1: Evolution of the broad nominal effective exchange rate index of the Pound sterling




**Note:** This figure illustrates the broad nominal effective exchange rate index of the Pound sterling. Source: Bank of England. Series name: XUMABK82. The value of the index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure. A decrease in the index corresponds to a depreciation of the Pound sterling.

Figure 2: Evolution of official consumer price indices for the United Kingdom




(a) Overall CPI

(b) CPI by category

**Note:** This figure shows selected consumer price indices for the United Kingdom. FMCG predominantly belong to the two categories 'Food and non-alcoholic beverages' and 'Alcoholic beverages, tobacco and narcotics'. The scanner dataset includes products from additional categories such as 'Clothing and footwear' and 'Furniture, household equipment and maintenance'. Source of the CPI series: Office for National Statistics. The value of the indices is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure.

Breinlich et al. (2021) investigate the effects of the Brexit-vote depreciation on living costs. Their analytical approach utilizes differences in import dependencies across product groups, which includes both direct consumer imports and the imported components utilized in local production. The study by Breinlich and colleagues indicates, via an event study approach, that the increase in inflation was more pronounced in product groups with significant import dependencies. This trend backs the argument that the Pound sterling's decline *caused* the inflationary period. The study further explores the correlation between exchange rates and consumer prices, acknowledging potential variations across product groups based on their import content. Their findings hint at a full long-term pass-through relative to a product group's import share. More specifically, a 1 percent depreciation corresponds to a 0.1 percent price increase for a product group with a 10 percent higher import dependency. As a result, the authors claim that the Brexit-vote depreciation had a notable upward effect on consumer prices in the UK. Under the assumption that product groups with zero import content remain untouched by currency fluctuations, the aggregate pass-through to consumer prices mirrors the UK's overall consumer expenditure on imports, which is 29 percent. This suggests that the Pound sterling depreciation following the Brexit vote, which was around 10 percent, caused consumer prices to jump by 2.9 percent, taking roughly two years for the full materialization of this effect.[2]

Breinlich et al. (2021)'s analytical approach resembles the strategy adopted by Gerstein et al. (2019), as both studies exploit variations in import dependencies across product groups to dissect the relationship

[2] Other research, such as the one by Corsetti & Crowley & Han (2022), utilize transaction-specific customs data to analyze the Brexit-vote depreciation's influence on border prices. Their analysis suggests that Pound sterling-invoiced import prices exhibited delayed reactions in comparison to those anchored to producer or vehicle currencies. Yet, approximately 36 weeks later, Pound sterling-invoiced import prices had adjusted fully to the weakened currency, leading to a fast and complete pass-through of the Brexit-vote depreciation to import prices.

between the Brexit-vote depreciation and consumer price inflation. Gerstein et al. (2019) reckon that if the surge in inflation post-referendum was primarily driven by the impact of the exchange rate, a marked disparity would be evident in the price shifts between tradable and nontradable products. This disparity would highlight the stronger sensitivity of tradable product import prices as compared to their nontradable counterparts. Through the application of difference-in-differences analysis, the study uncovers that approximately two-thirds of the inflationary surge in the UK post-referendum can be ascribed to the Brexit-vote depreciation. In their methodology, the control group encompasses products characterized by minimal import content, as derived from input-output tables, which are defined as nontradables. Conversely, the treatment group comprises products with substantial import content that fall under the tradable category. Given that such products are expected to be more sensitive to exchange rate fluctuations, they serve as the key measure to assess the pass-through to aggregate consumer prices. Their findings reveal a significant increase in relative prices for tradable products compared to their nontradable counterparts. Quantitatively, they derive that of the 1.9 percent increase in aggregate consumer prices in the eight months succeeding the referendum, about 1.2 percentage points can be attributed to the Brexit-vote depreciation. This suggests that approximately two-thirds of the inflation pickup is caused by the exchange rate change.

Dhingra & Sampson (2022) provide a literature review focusing on the economic effects of the Brexit referendum. They designate the period of June 2016 until end of 2020 as the 'waiting period'. Although the Brexit vote took place in June 2016, the UK–EU economic relationship remained unchanged until the beginning of 2021 when a new UK–EU free trade agreement came into force. Dhingra & Sampson (2022) assess the evolution of the Pound sterling as the main driver of consumer prices post-referendum. More specifically, they state that "*[t]he fall in the value of sterling following the referendum raised consumer prices and imported input costs, leading to a decline in real wages*" (p.497). This evaluation is based on the research of Breinlich et al. (2021), among other sources. Beyond the inflationary effects on consumer prices, Dhingra & Sampson (2022) find that the the Brexit vote exerted broad negative effects on the UK economy during the 'waiting period', as it led to lower investment, and slower real wage and GDP growth.

To examine the changes in prices of FMCG as reflected in the scanner dataset, I construct a scanner data-based price index for the years 2015, 2016 and 2017. More specifically, I mimic the method employed by the UK Office for National Statistics (ONS) to calculate the Consumer Price Index (CPI). The process involves the following steps:

1. Selection of a representative sample of products: I begin by selecting a representative sample of FMCG frequently purchased by households. This sample comprises all product-retailer pairs (PRP) transacted consistently in each month over the 2015 to 2017 period.

   To be more precise on the terminology throughout this paper, a PRP refers to a specific product being sold at a particular retailer. This means that the same product, when available at different retailers, is considered as separate PRP in the dataset. This approach allows me to capture potential retailer-specific variations in price, promotions, and other relevant factors. This is consistent with many standard conventions, including those by ONS, which recognize that identical products can have different prices depending on where they are sold. However, statistical authorities typically sample products across a variety of retailers to get a representative average price. By defining PRP, I allow for a more detailed assessment of price dynamics. On the downside, this implies further complexities. In particular, weighting becomes crucial to ensure that specific retailers or products do not disproportionately influence the results. This granular approach is not always the standard in national price indices, where broader categories and averages might be preferred due to data availability and computational constraints. In summary, while my approach aligns with the fundamental objectives of capturing price variations, the level of granularity I introduce by using PRP can offer more insights but also requires more sophisticated data handling and computation methods.

2. Price relative calculation: For each PRP in the basket, I compute a 'price relative', which represents the change in price compared to a base period.

3. Elementary aggregate construction: I aggregate these price relatives into 'elementary aggregates' using a weighted geometric mean.[3] The elementary aggregates I employ correspond to granular product categories. In other words, I calculate the weighted geometric mean of the price relatives within each category, where the weights are determined by the base period total expenditure on each PRP within a category, which is usually defined at a more granular level than COICOP's 5-digit sub-classes.

   To highlight this granularity, consider the following examples in the 'Food and non-alcoholic beverages' (FnB) section: Olive oil is further divided into the categories extra virgin, light, special and standard. White bread is further divided into the categories bagels, baguette, ciabatta, flatbread, focaccia, and more. Marmalade is differentiated by cut - fine cut, medium cut, pure fruit spread, thick cut and thin cut. Moreover, instant coffee turns into multiple categories like decaf freeze dried, freeze dried, granules, micro ground, speciality instant coffee, and others. The dairy section offers yoghurt categories including active, childrens, health, plain/natural, fat free, very low fat, low fat, soya/dairy free, and several more. And cheese is an extensive class leading to over 70 specific categories ranging from blue brie to wensleydale. In the household equipment division, the categorization remains just as thorough. For example, washing machine products encompass categories like gel, liquid, one shot capsule and powder, and household food wraps are further divided into the categories baking paper, cooking liners, foil, foil bags, ice-cube bags, toast bags, and several more.

4. Aggregate weighting and combination: I then combine the elementary aggregates into an overall FMCG price index. This involves calculating a weighted average of the elementary aggregates, where the

[3] It is worth noting that it is untypical for statistical authorities to incorporate weights at this early, granular stage of the calculation. This is primarily due to the unavailability of detailed expenditure data at the product level, which is essential for the assignment of accurate weights. Statistical authorities usually apply unweighted averages for these initial computations. However, the access to comprehensive expenditure data allows to diverge from these standard procedures to refine the accuracy of this analysis. As evidenced by Jaravel (2018), significant variations in expenditure shares primarily appear within product categories, and are especially pronounced across highly disaggregated products.

weights are determined by the base period total expenditure on each category.

In more formal terms, this is what I do: I begin with defining a representative sample of PRP $\overline{\Omega}$, which includes all PRP $i$ that are consistently transacted in each month over the 2015 to 2017 period. The representative sample of those PRP thus corresponds to a static basket. The products in the data set are defined via a product identifier assigned by the market research firm and data provider Kantar.[4] Table 1 provides an overview of the scanner dataset.

Table 1: Summary of the scanner dataset

| | **2015** | **2016** | **2017** |
|---|---|---|---|
| **Number of Products** | 144,976 | 143,329 | 124,282 |
| **Number of Retailers** | 83 | 79 | 78 |
| **Number of PRP** | 625,429 | 606,035 | 544,978 |
| **Number of Categories** | 2,088 | 2,129 | 2,106 |
| **Sum of Expense (in GBP)** | 76,521,705 | 73,298,043 | 70,414,820 |

**Note:** This table presents a summary of the scanner dataset, displaying the count of products transacted with positive unit values by year. Transactions with zero expense or units are excluded from the analysis. In this study, I define a product-retailer pair (PRP) as a unique combination of a specific product sold by a specific retailer. Therefore, the ratio of the number of PRP to the number of products provides an indication of the average number of retailers in which a specific product is sold.

Next, I compute the price relative $R_{it}$ for each PRP $i$ in each period $t$ relative to the base period $t_0$ (January 2015). Formally:

$$R_{it} = \frac{P_{it}}{P_{it_0}} \tag{1}$$

where $P_{it}$ denotes the price of PRP $i$ in period $t$.

I then aggregate these price relatives into elementary aggregates $E_{gt}$ for each product category $g$ at each period $t$ using a weighted geometric mean:

$$E_{gt} = \prod_{i \in \overline{\Omega}_g} R_{it}^{w_{it_0}} \tag{2}$$

where $\overline{\Omega}_g$ denotes the set of PRP in category $g$ that are transacted in each period, and $w_{it_0}$ equals the total expenditure on PRP $i$ in period $t_0$ divided by the total expenditure on the corresponding category in period $t_0$.

Finally, I calculate the overall FMCG price index $I_t$ for each period $t$ by taking a weighted geometric mean of the elementary aggregates. The weights $w_{gt_0}$ represent the expenditure share on each category $g$ in the base period $t_0$. Therefore, these weights do not adjust with changes in consumer spending patterns. Formally:

$$I_t = \prod_{g} E_{gt}^{w_{gt_0}} \tag{3}$$

where $w_{gt_0}$ equals the total expenditure on category $g$ in period $t_0$ divided by the total expenditure on all categories in period $t_0$.

[4] More specifically, I utilize data from the Kantar Fast-Moving Consumer Goods Purchase Panel, a leading repository for household scanner data, comparable to the well-known Nielsen Homescan Consumer Panel, which is predominately used for academic research.

The resulting FMCG price index provides a measure of price changes for the static basket of PRP over time, using the expenditure patterns from January 2015 as the reference. In doing so, the index isolates and measures the extent of price changes within the specific selection of PRP, thereby excluding potential effects of fluctuating quantities. The choice of the base period implies that I evaluate the cost of purchasing the January 2015 basket of frequently transacted PRP over time.

The price index is depicted in Figure 3. The value of the index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure. Prior to the referendum, depicted on the left side of the vertical line, prices exhibited a downward trend. However, after the referendum, shown on the right side of the vertical line, prices started to move upward (with a delay of 4 months).

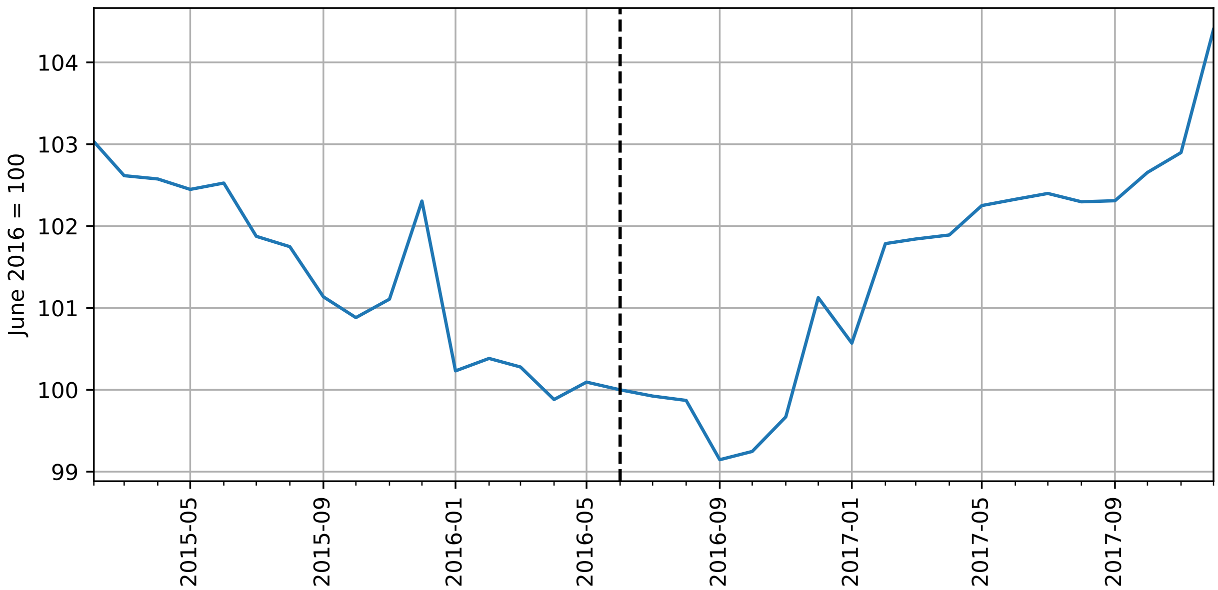
Breinlich et al. (2021, p.75) draw a comparison between the overall CPI in the UK and that in the Euro area. They interpret the relative increase in the UK's consumer prices, compared to the Euro area, as indicative of the post-Brexit depreciation's inflationary impact on the UK. While the scanner dataset does not extend to FMCG price movements in the Euro area, thus limiting a direct comparison, the distinct upward movement in UK FMCG prices after the referendum does provide some descriptive evidence in support of the view that the Brexit-vote depreciation has had inflationary effects, as stated by Breinlich et al. (2021), Gerstein et al. (2019) and Dhingra & Sampson (2022).

One notable feature of the FMCG price index are seasonal patterns. Prices always exhibit a surge in December, followed by a drop in January, and the summer months (i.e. June to September) mark the most deflationary period within a year. Furthermore, the FMCG price index aligns quite closely with the officially published CPI in the categories of 'Food and non-alcoholic beverages' and 'Alcoholic beverages, tobacco and narcotics', as shown in Figure 2b.[5] A U-shaped pattern in the FnB price index is particularly noticeable. Additionally, a distinct break in the inflation trend post the Brexit referendum is evident, both in panels 2a and 2b, aligning with the observations made from the FMCG price index. In addition, the numbers match, i.e. the FMCG index decreases from 103 in February 2015 to 100 in June 2016, and then increases to approximately 104 in December 2017. Very similar numbers can be observed for the FnB price index. This close alignment between the FMCG price index and the officially published CPI, particularly in the respective categories, provides a strong validation of the quality and reliability of the scanner data. The similarity suggests that the data accurately captures the underlying economic trends and gives credence to the results obtained from this analysis.

Utilizing a static basket of products and static expenditure weights holds several advantages when constructing a price index. Most importantly, this method provides a consistent framework for comparison of prices over time, eliminating the potential complications brought about by changing product varieties or evolving consumer preferences. This consistency makes it possible to isolate and focus solely on the price variations, thereby facilitating a clear analysis of price movements.

[5] As noted above, FMCG predominantly belong to the categories 'Food and non-alcoholic beverages', 'Alcoholic beverages, tobacco and narcotics', 'Clothing and footwear' and 'Furniture, household equipment and maintenance'. As per the most recent CPI weights published by the ONS, these four categories represent 24.4 percent of total household expenditure in the UK.

Figure 3: Evolution of the FMCG price index with a static basket and static weights




**Note:** This figure illustrates the FMCG price index, which is computed based on a sub-sample of 46,680 continuously transacted PRP on a monthly basis from 2015 to 2017. The products are classified into 1,501 distinct categories. The price index is calculated using the equations (1) to (3). The value of the index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure.

However, this approach also carries certain limitations. Primarily, it fails to reflect the dynamic nature of consumer behavior or product availability over time. For example, consumers might switch products in response to changes in relative prices, or new products might enter the market while old ones disappear. These dynamics can introduce a bias, potentially leading to an overstatement of inflation if the static basket does not account for consumers substituting towards relatively cheaper products. Moreover, the static expenditure weights might not accurately represent the actual spending patterns in subsequent periods. If the base period weights are exceptional, e.g., due to seasonal patterns, their application to succeeding periods might be misleading as they do not accurately represent typical consumption patterns

To address these potential biases, two modifications can be considered. First, dynamic weights may be applied: Instead of using the base-period weights, I can update the weights in each period based on the corresponding expenditure data. This approach would ensure that the price index accurately reflects the economic significance of each product in the consumers' basket over time. Second, a dynamic basket may be utilized: Instead of using a fixed basket of products, I can consider a dynamic basket that accommodates changes in product varieties and consumer preferences over time. This would involve including newly introduced products and excluding obsolete ones. By doing this, the price index would remain relevant and representative of the changing market conditions.

In order to implement dynamic weights, I calculate expenditure shares for each PRP and each category in every period, rather than just the base period. That is, the weights for the aggregation of price relatives into elementary aggregates would change in each period, as would the weights for the aggregation of elementary aggregates into the overall price index, both reflecting the changing expenditure patterns over time.

I begin with defining a representative sample of PRP $\overline{\Omega}$, which includes all PRP $i$ that are consistently transacted in each month over the 2015 to 2017 period, just like before. Next, I compute the price relative $R_{it}$ for each PRP $i$ in each period $t$ relative to the base period $t_0$ (January 2015), also just like before (see equation (1)).

I then aggregate these price relatives into elementary aggregates $E_{gt}$ for each category $g$ at each period $t$ using a weighted geometric mean. However, this time, the weights are updated in each period:

$$E_{gt} = \prod_{i \in \overline{\Omega}_g} R_{it}^{w_{it}} \tag{4}$$

where $\overline{\Omega}_g$ denotes the set of PRP in category $g$ that are transacted in each period, and $w_{it}$ equals the total expenditure on PRP $i$ in period $t$ divided by the total expenditure on the corresponding category in period $t$.

Finally, I calculate the overall FMCG price index $I_t$ for each period $t$ by taking a weighted geometric mean of the elementary aggregates, again with weights updated in each period:

$$I_t = \prod_{g} E_{gt}^{w_{gt}} \tag{5}$$

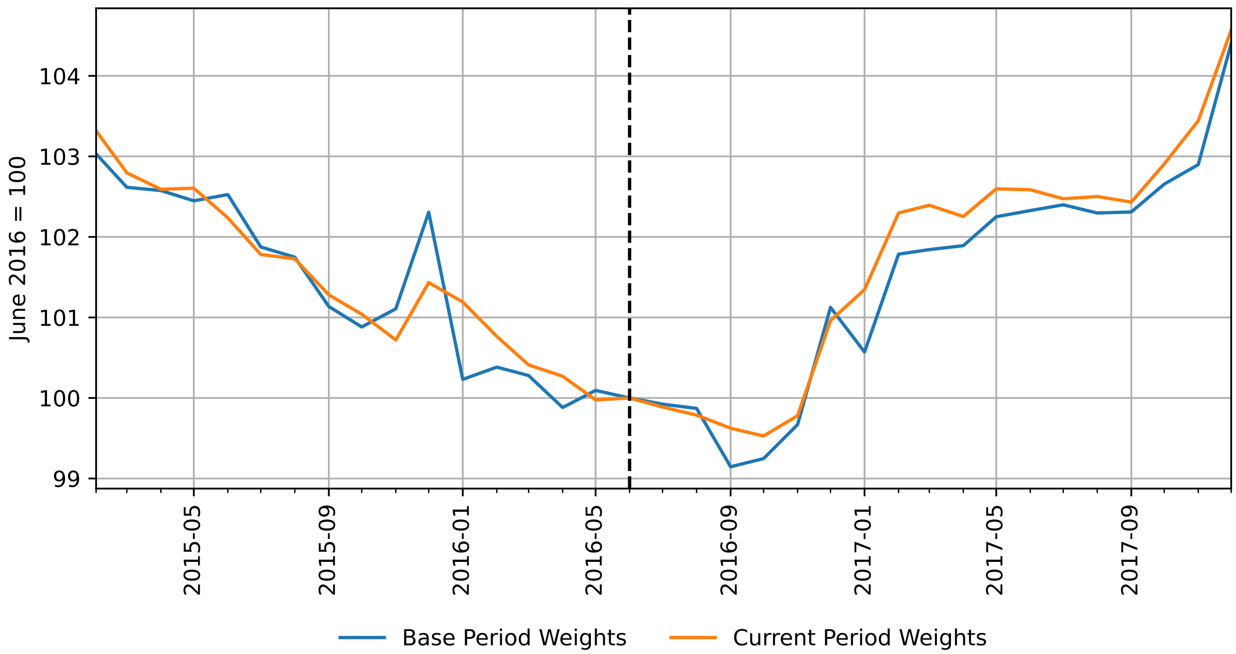
where $w_{gt}$ equals the total expenditure on category $g$ in period $t$ divided by the total expenditure on all categories in period $t$.

This results in an overall price index that takes into account not only changes in prices, but also changes in expenditure patterns over time. This FMCG price index, alongside the FMCG price index computed with static weights, is displayed in Figure 4. The resulting series are nearly identical indicating that changes in consumer spending patterns over time have not significantly affected the overall price movements based on a static product basket. Therefore, the relative expenditure on different PRP and categories appears to remain relatively constant over time.

In order to implement a dynamic basket, a 'matched model' approach is utilized, wherein only those PRP that have records in both the current and previous month are considered for the price index calculation. This implies that the representative sample of PRP $\Omega_t$ is refreshed in each month $t$, as shown in Figure 5. Notably, the figure reveals that the number of PRP transacted in two adjacent periods decreases over time, especially in 2017. This corroborates the Bank of England's finding of a sharp contraction in retail spending starting at the transition from 2016 to 2017, as documented by Broadbent (2017).

The matched model approach helps to account for the dynamics in the market and changing consumer preferences over time and allows the price index to maintain its relevance by consistently adapting the basket to market conditions. However, it is important to note that while this method accounts for changing patterns

Figure 4: Evolution of the FMCG price index with a static basket: Base period weights vs. current period weights




**Note:** This figure illustrates FMCG price indices, which are computed based on a sub-sample of 46,680 continuously transacted PRP on a monthly basis from 2015 to 2017. These products are classified into 1,501 distinct categories. The value of each index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure. The price indices using base period weights and current period weights are calculated using the equations (1) to (5).

of products, it does not capture the immediate effect of entirely new products entering the market.[6]

To construct such a matched model price index, I first compute the price relative $R_{it}$ for each PRP $i$ that is part of the sample of PRP $\Omega_t$ in each period $t$ relative to the previous period $t-1$. Formally:

$$R_{it} = \frac{P_{it}}{P_{it-1}} \tag{6}$$

where $P_{it}$ denotes the price of PRP $i$ in period $t$.

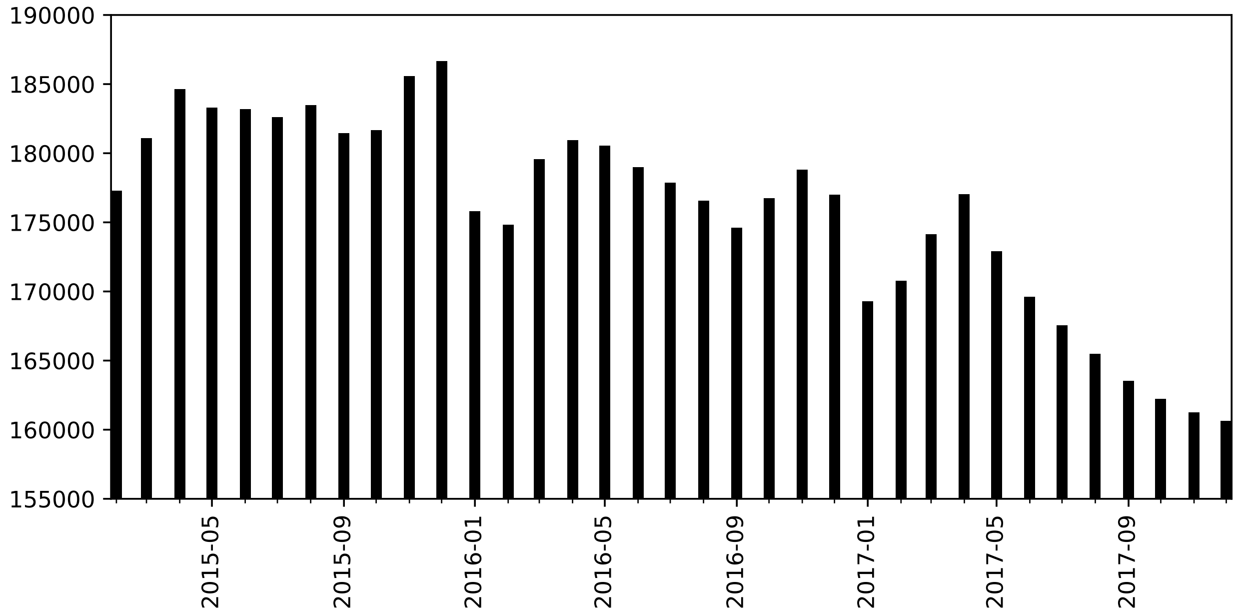
I then aggregate these price relatives into elementary aggregates $E^L_{gt}$ for each category $g$ at each period $t$ using a weighted geometric mean:

$$E^L_{gt} = \prod_{i \in \Omega_{gt}} R_{it}^{w_{it-1}} \tag{7}$$

where $\Omega_{gt}$ denotes the set of PRP in category $g$ that are transacted in periods $t$ and $t-1$, and $w_{it-1}$ equals the total expenditure on PRP $i$ in period $t-1$ divided by the total expenditure on the corresponding category in period $t-1$. The superscript $L$ is used to designate that this is a Laspeyres-type index. This implies that the weights used for aggregation are sourced from the base period (which equals the previous period in a

[6]While a matched model approach with monthly refreshment of the product sample provides a more dynamic depiction of market changes, capturing the full spectrum of market adjustments and consumer behavior would require more complex methodologies that deal with the introduction of new products. This is the subject of Section 3.3..

Figure 5: Temporal evolution in the count of PRP in two adjacent periods




**Note:** This figure illustrates the number of PRP that have records in both the current and previous month, i.e. it shows the sub-sample of PRP $\Omega_t$.

matched model approach), inherent to the Laspeyres method.

Finally, I calculate the FMCG price index values $I_t^L$ for each period $t$ by taking a weighted geometric mean of the elementary aggregates. The weights $w_{gt-1}$ represent the total expenditure on each category $g$ in the previous period $t-1$. Consequently, these weights are sensitive to changes in consumer spending patterns, as they are updated based on the observed expenditure distribution across different categories from the preceding period. Formally:

$$I_t^L = \prod_g {E_{gt}^L}^{w_{gt-1}} \tag{8}$$

where $w_{gt-1}$ equals the total expenditure on category $g$ in period $t-1$ divided by the total expenditure on all categories in period $t-1$.

The price index values I calculated for each period $t$ capture the dynamics inherent in the retail market. They account for changes in the product availability, prices, and quantities consumed, as well as evolving consumer behaviors and expenditure patterns. However, these price index values represent a chain-type index, where each period is compared to the preceding period, not to a fixed base period. Thus, this kind of index effectively captures the fluctuations and trends in two adjacent periods, yet it does not directly provide a comprehensive view of price changes relative to a base period over an extended timescale. To transform these individual index values into a chained index series that reflects price changes relative to a base period, I cumulatively multiply the index values – essentially 'chaining' them together – which creates a continuous series of index values.

This Laspeyres-type price index, while being an effective tool for assessing price changes over time, does come with a few shortcomings. Most notably, using previous period weights can lead to overestimation of the price index when prices increase, as it does not account for the tendency of consumers to substitute towards less expensive products. To address this limitation, the Fisher price index, a geometric mean of a Laspeyres-type and Paasche-type price index, is commonly used. The Fisher price index considers both current and previous period weights, thereby better reflecting consumer substitution behavior. This makes the Fisher price index more flexible and adaptive, capturing price changes more accurately in a dynamic market environment. In addition, the Fisher price index mitigates the potential upward bias of a Laspeyres-type price index and the downward bias of a Paasche-type price index, hence making it a more balanced and reliable measure of price changes.[7]

In the process of calculating the Fisher price index, I construct a Paasche-type price index, which I then harmonize with the previously computed Laspeyres-type price index. Initially, using the same price relatives derived from equation (6), I aggregate them into elementary aggregates $E_{gt}^{P}$ for each category $g$ during each time period $t$. This aggregation is done using a weighted geometric mean, but with the weights $w_{it}$ now corresponding to the current period. In formal terms:

$$E_{gt}^{P} = \prod_{i \in \Omega_{gt}} R_{it}^{w_{it}} \tag{9}$$

where all the definitions from equation (7) hold, except for $w_{it}$, which now signifies the proportion of total expenditure on PRP $i$ during period $t$ in relation to the total expenditure within the corresponding category during the same period. The superscript $P$ denotes that this is a Paasche-type price index, which relies on the use of weights derived from the current period for aggregation.

Following the computation of elementary aggregates, I derive the FMCG price index values $I_t^P$ for each period $t$. This is achieved by taking a weighted geometric mean of the elementary aggregates:

$$I_t^P = \prod_{g} E_{gt}^{P\, w_{gt}} \tag{10}$$

where $w_{gt}$ stands for the ratio of total expenditure on category $g$ during period $t$ to the total expenditure across all categories during the same period. The final step is the generation of a chained series of index values, which is accomplished by the cumulative multiplication of the individual index values.

Having obtained both the Laspeyres and Paasche-type price indices, I proceed to compute the Fisher price index:

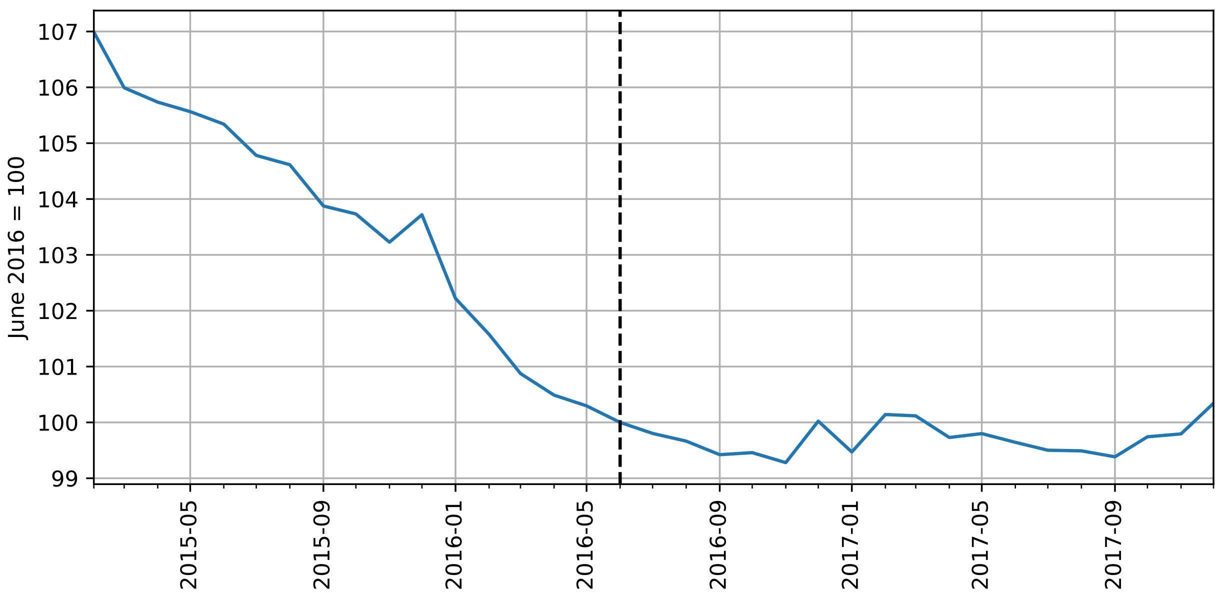
$$I_t^F = \sqrt{I_t^L \cdot I_t^P} \tag{11}$$

[7] As stated in Graf (2020, p.3), "*the superlative indices Walsh, Fisher, and Törnqvist show up as being "best" in all the approaches to index number theory. These three indices give very similar results so that for any practical reason it will not make any difference which one is chosen as the preferred theoretical target index because they most closely approximate a COLI [Cost of Living Index]*".

Thus, the Fisher price index is computed as the geometric mean of the Laspeyres and Paasche-type price indices, thereby compensating for the potential biases inherent in each of the two price indices when considered individually.

This Fisher price index, with the index value set to 100 in June 2016, is illustrated in Figure 6. The evolution of the Fisher price index reveals an interesting pattern: it records a decrease of 7 index points in the one-and-a-half years preceding the Brexit referendum, and exhibits a sideways movement in the one-and-a-half years following the event.

Figure 6: Evolution of the FMCG Fisher price index (dynamic basket)




**Note:** This figure illustrates the FMCG Fisher price index, which is computed based on a sub-sample of PRP $\Omega_t$ that is refreshed in each month $t$ as shown in Figure 5. These products are classified into 2,143 distinct categories. The price index is calculated using the equation (11) based on a Laspeyres and Paasche-type price index as outlined in equations (6) to (8) for the Laspeyres-type price index, and (6) as well as (9) to (10) for the Paasche-type price index. The value of the index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure.

Assessing the findings thus far, I have come to observe several key features in the price evolution of the FMCG sector. These features are derived from the three distinct methodologies employed in calculating price indices: Static basket with static weights, static basket with dynamic weights, and dynamic basket with dynamic weights.

The static basket with static weights index represents the most simplistic approach to calculating the price index, relying on a consistent set of products and their corresponding weights based on a specified base period. The strength of this approach lies in its ability to offer a direct comparison of prices over time, devoid of any consideration for shifts in consumer behavior or market conditions. The analysis shows that this index experienced a significant increase in prices following the Brexit referendum, while it experienced a significant decrease in prices prior to the Brexit referendum.

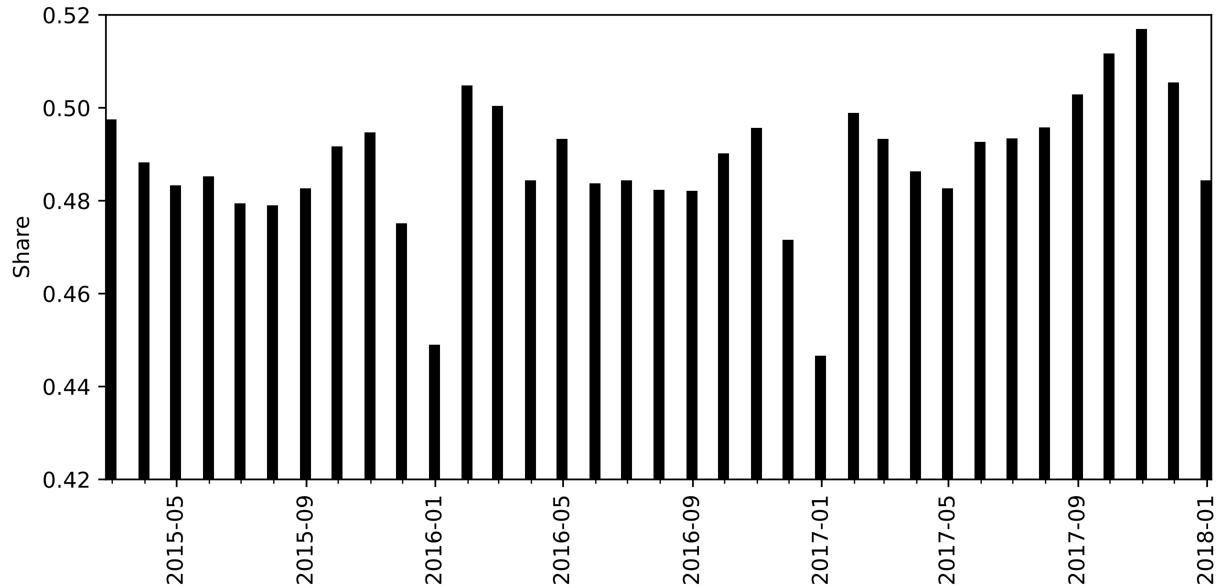
The static basket with dynamic weights index, on the other hand, considers changes in consumer expenditure patterns over time, while maintaining a consistent set of products. The weights, in this case, are adjusted periodically to mirror changes in consumer spending. This index also indicates a notable increase in prices post-referendum, and a decrease in prices prior to the referendum. This implies that even when accounting for changes in consumer spending patterns, the prices of a fixed set of products increased more sharply after the referendum compared to the period preceding it.

Lastly, the dynamic basket with dynamic weights index provides the most complex approach. By considering changes in both the set of products and expenditure weights over time, this methodology captures shifts in consumer behavior and market conditions. In line with the previous indices, the Fisher price index records a decline in prices leading up to the referendum. However, the post-referendum period now reveals a different picture: Instead of the pronounced price increase observed in the other indices, the Fisher price index displays a mostly lateral movement of prices. Thus, while the referendum period still seems to act as a demarcation point, resulting in a change of direction for the trend, it does not lead to an upward movement of prices, but to a horizontal movement of prices.

This observed difference in price movements post-referendum as captured by the Fisher price index (dynamic basket with dynamic weights) compared to the other two price indices (static basket with static or dynamic weights) may point to a change in the basket of products and/or a corresponding adjustment of spending patterns. The Fisher index considers changes in the set of products over time, which can reflect the entry of new products, the exit of old products, and changes in the popularity of different products. If new, less expensive products have entered the market or become more popular after the Brexit referendum, perhaps in response to economic uncertainty or (expected) income effects, they could contribute to keeping the overall price index stable.

Figure 7 shows that the expenditure share on consistently transacted PRP lies between 44 and 52 percent and is relatively stable over the period from 2015 to 2017. The finding suggests that there is a significant portion of expenditure that is allocated to PRP not consistently transacted on a monthly level over this time frame. This could represent PRP that have been newly introduced, re-appearing, phased out, or whose popularity has fluctuated significantly. Such a dynamic product environment, which is a common observation with scanner data (see, e.g., Chessa & Verburg & Willenborg, 2017), can result in differing price movements, particularly when comparing indices that account for this dynamic basket of products (like the computed Fisher price index) to those that do not (static basket price indices). This fact further emphasizes the importance of adapting product availability and consumer preferences when analyzing (aggregate) price movements. However, while standard matched model approaches like the computed Fisher price index take these variables into account, certain aspects of market adjustments remain uncaptured, such as extensive margin adjustments, which refer to the situation where prices for newly introduced or re-appearing products are unobserved in the preceding period, preventing the computation of a price relative. Extensive margin adjustments, along with evolving consumer behavior, can considerably distort the representation of price changes, potentially masking the actual impact of FMCG price movements, especially in pivotal periods like the Brexit referendum. Therefore, it is important to delve further into this aspect to gain a more comprehensive understanding of the micro-level price evolution around the time of the Brexit referendum. To explore the effects of extensive margin adjustments will be the goal of the next section.

Figure 7: Evolution of the expenditure share on consistently transacted PRP over time




**Note:** This figure illustrates the importance of the set of PRP $\overline{\Omega}$, which includes all PRP $i$ that are consistently transacted in each month over the 2015 to 2017 period, over time. More specifically, I compute the total expenditure share on the set of PRP $\overline{\Omega}$ for each month $t$. To do so, I take the total expenditure on the set of PRP $\overline{\Omega}$ and divide it by the total expenditure on the set of PRP $\Omega_t$, which comprises those PRP that have records in both the current and previous month, i.e. the set of PRP $\overline{\Omega}$ plus further PRP that are transacted in both months $t$ and $t-1$, but not in each month over the 2015 to 2017 period. The 46,680 PRP that are consistently transacted account for a total expenditure share of 0.44 to 0.52. This is a relatively high share when considering the number of PRP transacted in two adjacent periods, as shown in Figure 5, which ranges from 160,000 to 190,000.

## 3.3. The role of extensive margin adjustments

Extensive margin adjustments, which encompass the introduction of new products to the market, the re-appearance of products that have not been transacted for some time, and the withdrawal of existing ones, can significantly affect price changes. These changes often go unnoticed in standard price indices because price relatives for newly introduced or re-appearing products cannot be computed, given that these product prices are unobserved in the period preceding their introduction or re-appearance.

Nakamura & Steinsson (2012) highlight a related challenge, asserting that conventional matched model price indices cannot accurately capture the full linkage between prices and exchange rate movements due to a 'product replacement bias', as price adjustment that occur at the time of product replacements are 'lost in transit'. They empirically demonstrate this bias using US import and export price index micro-data and propose a model to explain it.

In scanner data analysis, the inaccurate measurement of price changes that occur when an established product is replaced with a similar, usually more expensive alternative, is typically defined as the 'relaunch problem' (Daalmans, 2022). A relaunch is often accompanied by minor alterations in the product's external appearance, such as packaging modifications. Relaunches frequently occur in the FMCG market, and thus ignoring them can have severe consequences for the measurement of price changes. For example, Chessa (2016b) reveals that the neglect of relaunches can lead to a large bias in inflation figures. To mitigate this bias, a popular strategy involves categorizing products with identical or analogous characteristics into product clusters/groups, and to treat these groups as a single entity. Subsequently, a price index is calculated from the product groups, rather than from the underlying products. Product clustering is, however, only appropriate for sufficiently homogeneous products, otherwise it may lead to unit value bias, as noted by Diewert & Lippe (2010), among others.

The significance of the extensive margin in the accurate measurement of inflation is also underscored by Eichenbaum & Jaimovich & Rebelo (2011). Their analysis, based on scanner data, reveals that prices tend to be rigid, with non-sale prices frequently remaining stable for a year or more. Consequently, price changes which occur during a product's (re-)entry into the market are potentially a crucial source of price fluctuations.

Especially with newly introduced products in form of 'successions', it is commonly observed that they enter the market at a higher price than their predecessors. Therefore, the initial task is to identify successions within the dataset in order to then assess the scope of a potential 'succession bias' in standard price indices.[8]

Successions typically occur when a product is phasing out and a new product – often with slightly differing packaging or attributes – takes its place. I define three main forms of successions. First, direct successions, which occur when a new product, from the same manufacturer and bearing identical characteristics as the established one, is introduced in the same retailer. Second, volume-adjusted direct successions, in which the new product from the same manufacturer sold in the same retailer is bearing identical characteristics except for the package volume. Third, similar product successions, which refers to instances where a product with similar – but not necessarily identical – characteristics, possibly from a different manufacturer and with a different package volume than the established one, but sold in the same retailer, is introduced. Once the successions are identified, I can track the price levels of the established product prior to the successor's introduction and then compare these to the price levels of the successor upon their introduction. If I observe an average increase in price levels, it indicates an inflationary effect of successions on the overall price evolution.

In constructing the elementary aggregates, I benefit from a more extensive selection of products than the

[8]In this study, the term 'succession' is used in a specific way to denote the introduction of a new product that shares identical or similar characteristics with at least one established product. This does not imply that the new product necessarily discontinues or directly replaces the older one. It is possible that both products co-exist on the shelves for some time. A new product might also represent a completely novel item, not seen before in the market. However, if there is an established product with identical or similar characteristics, I categorize the new product as a successor. This is because the characteristics are defined very narrowly, and thus a match in these characteristics indicates that the new product is likely intended as a replacement or alternative to the established one. Thus, with the term succession, I seek to highlight that the new product is either a continuation or progression from an earlier product, even if the previous one has not been phased out yet. A new product potentially being an alternative to an existing one also explains why I do not adopt the term 'replacement bias' from Nakamura & Steinsson (2012) or 'relaunch problem' from Daalmans (2022).

sub-sample traditionally used by many statistical authorities. This abundant data enables me to capture a comprehensive view of market dynamics, and thus I can capture all three succession types as described above. Although tracking the like-for-like price changes specific to direct succession is the cleanest way to capture succession effects[9], I recognize that volume-adjusted direct successions and similar product successions can still play a significant role. The absence of a direct predecessor for many newly introduced PRP means that neglecting their introductory prices would leave out key market segments, especially when consumer preferences shift significantly towards those PRP. Given the significance of both volume-adjusted and similar product successions, I incorporate them alongside direct successions, ensuring a comprehensive analysis of all three dimensions.

I proceed as follows: The initial step involves evaluating the impact of successions on the overall price evolution. This is achieved by examining whether the prices at which new PRP are introduced are, on average, higher than the prices of identical or similar established PRP from the previous period. To make this comparison, I construct price relatives for each of the three types of successions. In the context of direct successions, I consider a PRP as a successor only if it shares identical characteristics with at least one established PRP across all dimensions. This ensures that I am comparing like with like as closely as possible. For volume-adjusted direct successions, I am slightly more flexible and allow the PRP to differ in their package sizes. With similar product successions, I broaden the definition of successions even further to include all PRP within narrowly defined categories as potential successors, allowing for some variation in the product characteristics. The less restrictive the definition of a successor is, the more successions can be identified, i.e. the more price relatives can be computed that are not directly observable in the dataset, but which can have an impact on the overall price evolution. Once I have computed the price relatives for these three types of successions, I construct a Fisher price index that includes the computed price relatives at the point of the successor introductions. This price index is essentially a matched model approach that accounts for all three types of successions. Finally, I compare this successions-adjusted Fisher index to a baseline Fisher price index that does not account for any type of succession.

It is important to emphasize that this methodology establishes product groups only when deemed necessary, resulting in a limited number of price relatives being derived from these groups. This strategy makes it possible to predominantly utilize PRP price relatives, thereby addressing the relaunch problem as discussed in Daalmans (2022), without putting to much emphasis on the product groups.

In the subsequent analysis, I build on a similar method and construct a Fisher price index that not only accounts for newly introduced PRP but also integrates re-appearing PRP. By adopting this extended approach, I seek to fully capture the 'extensive margin bias' present in conventional price indices, considering

[9] Tracking the like-for-like price changes specific to direct successions circumvents the complications posed by volume-adjusted direct successions and similar product successions, such as that smaller volume packages might often be under-proportionally cheaper than their larger counterparts, mismatches in quality between the established product and its substitute, or differing price dynamics due to changes in market conditions, supply chain factors, or demand shifts. Furthermore, imperfect substitutes may not provide the same utility to the consumer as the original product, and this difference could be reflected in a price discrepancy.

every conceivable price relative that cannot be determined directly.[10]

Given that I will group PRP together with different product identifiers, but with identical or similar characteristics, and that I will employ unit prices (e.g., price per millilitre or price per gram) instead of unit values, some data cleaning is required. First, I eliminate products measured in 'Pieces' due to observed discrepancies in volume among near-perfect substitutes. For instance, while two chewing gums appear identical in all specified characteristics – including their measurement unit of 'Pieces' and the volume labeled as 'Single' – there is an underlying disparity in the package size. The descriptions clarify that one pack contains 120 pieces while the other holds only 36. Second, I eliminate products without a brand name, as brand identification is required to properly group products together. Third, volume information serves as a critical criteria in product comparison. Thus, any product with no volume description or an ambiguous volume description like 'Loose', 'Random Weight', 'All Other Sizes', or 'Standard' is excluded. The impact of these data cleaning steps on the sample size can be observed in Table 2.

Table 2: Summary of complete and reduced scanner dataset sample

| | **Complete** | **Reduced** | **Change** |
|---|---|---|---|
| **Number of Products** | 186,111 | 125,368 | -33% |
| **Number of Retailers** | 83 | 82 | -1% |
| **Number of PRP** | 982,949 | 671,389 | -32% |
| **Number of Categories** | 2,197 | 1,633 | -26% |
| **Sum of Expense (in GBP)** | 220,234,568 | 160,159,134 | -27% |

**Note:** This table presents a comparison of the complete and reduced scanner dataset sample spanning the years 2015-2017. Information on the complete scanner dataset sample by year can be found in Table 1.

I start by analyzing the effects of direct successions. To identify direct successions, I first establish product groups in which the PRP exhibit identical characteristics. More specifically, each group consists of PRP that share the same brand, are manufactured by the same entity, possess identical attributes, fall within the same category, are measured in the same unit, and have an equivalent package volume or size. Examples of such groupings are illustrated in Table 3.

Throughout the period of 2015 to 2017, I find that ca. 90,000 PRP fall into product groups that contain at least two distinct PRP. This finding suggests the presence of numerous direct successions within the dataset. PRP within the same group are treated as direct successors for the following reason: If there is an established PRP with identical characteristics, it indicates that the new PRP is likely intended as a replacement or alternative to the established one (and thus a direct successor), even if the two PRP co-exist in the market for some time.

The quantity of PRP decreases as the number of PRP within a group increases. More than 550,000 groups consist of just one PRP. About a tenth of that contains exactly two PRP. Even fewer (ca. 19,000 groups) are made up of three distinct PRP, while the rest (ca. 18,000 groups) have four or more. On average, a group contains 1.23 PRP.

[10]Incorporating both newly introduced and re-appearing PRP into the analysis offers a comprehensive approach to capturing unobserved price relatives. While integrating the newly introduced PRP already enhances the scope beyond just considering replacement products, factoring in re-appearing PRP further extends the coverage of previously unobserved price relatives, offering a more comprehensive perspective on price dynamics.

Table 3: Examples of PRP to product groups mapping

| Product ID | Retailer ID | Brand | Subbrand | Manufacturer | Attributes | Category | Volume | Description | Group |
|---|---|---|---|---|---|---|---|---|---|
| 867647 | 111 | Kelloggs | Klgs Crunchy Nut Cluster | Kellogg Co.of G B Ltd | Ready To Eat Breakfast Cereals, Packet Breakfast | Ready To Eat Cereals | 450 Gm | KLGS CRNCHY NT CLSTR HNY 450GM | 4307 |
| 867647 | 117 | Kelloggs | Klgs Crunchy Nut Cluster | Kellogg Co.of G B Ltd | Ready To Eat Breakfast Cereals, Packet Breakfast | Ready To Eat Cereals | 450 Gm | KLGS CRNCHY NT CLSTR HNY 450GM | 4308 |
| 867653 | 111 | Kelloggs | Klgs Crunchy Nut Cluster | Kellogg Co.of G B Ltd | Ready To Eat Breakfast Cereals, Packet Breakfast | Ready To Eat Cereals | 450 Gm | KLGS CRNCHY NT CLST C/CRL 450G | 4307 |
| 867653 | 117 | Kelloggs | Klgs Crunchy Nut Cluster | Kellogg Co.of G B Ltd | Ready To Eat Breakfast Cereals, Packet Breakfast | Ready To Eat Cereals | 450 Gm | KLGS CRNCHY NT CLST C/CRL 450G | 4308 |
| 433578 | 127 | Kelloggs | Klgs Crnchy Nt Crnflk | Kellogg Co.of G B Ltd | Ready To Eat Breakfast Cereals, Packet Breakfast | Ready To Eat Cereals | 500 Gm | KELLOGGS CNCHY NUT CRNFLK500GM | 4300 |
| 871768 | 117 | Kelloggs | Klgs Crnchy Nt Crnflk | Kellogg Co.of G B Ltd | Ready To Eat Breakfast Cereals, Packet Breakfast | Ready To Eat Cereals | 500 Gm | KELLOGGS CNCHY NUT CRNFLK500GM | 4299 |
| … | … | … | … | … | … | … | … | … | … |
| 776628 | 111 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 160 Gm | HARIBO MAOAM STRIPES BAG 160GM | 120980 |
| 784840 | 111 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 160 Gm | HARIBO GOLD BEARS BAG 160GM | 120980 |
| 776628 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 160 Gm | HARIBO MAOAM STRIPES BAG 160GM | 120985 |
| 784840 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 160 Gm | HARIBO GOLD BEARS BAG 160GM | 120985 |
| 793606 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 160 Gm | HARIBO MAOAM HPPY FRTTI BG160G | 120985 |
| 392449 | 111 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO MAOAM STRIPES BAG 200GM | 121083 |
| 906940 | 111 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO MAOAM JOY STX BAG 200GM | 121083 |
| 957257 | 111 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO MAOAM SR STRIPES BG200G | 121083 |
| 416132 | 111 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO GOLD BEARS BAG 200GM | 121083 |
| 392449 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO MAOAM STRIPES BAG 200GM | 121087 |
| 416132 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO GOLD BEARS BAG 200GM | 121087 |
| 798727 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO MAOAM HPPY FRTTI BG200G | 121087 |
| 906940 | 127 | Haribo | Haribo Fruits | Dunhills P L C | Take Home Sugar Confectionery | Sugar Fruit Candies | 200 Gm | HARIBO MAOAM JOY STX BAG 200GM | 121087 |

**Note:** This table presents a selection of 16 products from the dataset, providing an overview of their detailed characteristics. I define a product-retailer pair (PRP) as a unique combination of a specific product sold by a specific retailer. This implies that the first two products displayed in the table, despite having the same product id, are treated as distinct PRP in the dataset due to their affiliation with different retailers. This retailer-specific approach also clarifies why these two products do not belong to the same group, even though all their other characteristics are identical. The third product in the list is grouped together with the first one since all its characteristics, including the retailer, are identical. One noteworthy point is the semantic similarity of the descriptions of these two products, despite the syntactic differences. Such minor differences in textual descriptions pose a challenge for product matching when description is used as a matching parameter. Accordingly, in this methodology, products are grouped based on an exact match of the following characteristics: Product ID, Retailer ID, Brand, Subbrand, Manufacturer, Category, Attributes, and Volume, but not on an exact match of Description. This approach leads to instances where products with distinct flavors or styles are classified within the same group. As an example, 'Haribo Maoam' and 'Haribo Gold Bears' are categorized in the same group when all their characteristics align. This implies that in this analysis, 'Haribo Maoam' can potentially be a successor for 'Haribo Gold Bears'.

Having grouped direct successors, I can proceed with the analysis to investigate the presence of systematic price dynamics upon the introduction of successors. More specifically, my objective is to assess whether the introduction price of a successor is systematically higher than the price of their established near-perfect substitute(s). This analysis helps to understand if there are systematic pricing strategies associated with direct successions, which could shed light on manufacturers' and retailers' practices concerning successor product pricing, and the potential influence of direct successions on the observed pricing dynamics around the Brexit referendum.

As a first step, I create a price ratio of a newly introduced PRP and the weighted average price of established PRP within its group:

$$\hat{P}_{ijt} = \frac{P_{ijt}}{GM_{jt-1}} \tag{12}$$

where $P_{ijt}$ is the price of a newly introduced PRP $i$ in group $j$ in period $t$, and $GM_{jt-1}$ is the weighted geometric mean of the prices of established PRP within the same group $j$ in period $t-1$. $\hat{P}_{ijt}$ is the resulting price ratio. I identify newly introduced PRP based on two criteria. First, the PRP is transacted for the very first time in the dataset and second, the product id was not observed in the years prior to 2015, as confirmed by the barcode dictionary that lists products transacted up to the end of 2014. It is worth noting that the establishment of $\hat{P}_{ijt}$ implies that near-perfect substitutes were transacted before the new PRP introduction, and thus it can be interpreted as the price ratio of a newly introduced PRP.

The weighted geometric mean is computed as:

$$GM_{jt-1} = \prod_{i \in j} P_{it-1}^{w_{it-1}} \tag{13}$$

where $w_{it-1}$ stands for the ratio of total expenditure on PRP $i$ during period $t-1$ to the total expenditure across all PRP in group $j$ during the same period.

Table 4 presents the distribution of the price ratio $\hat{P}_{ijt}$. The mean is 1.04, indicating that newly introduced PRP are typically priced higher than the average of their near-perfect substitutes in the prior period. This upward price trend indicates inflationary pressures from direct successions.

Table 4: Distribution of the price ratio $\hat{P}_{ijt}$

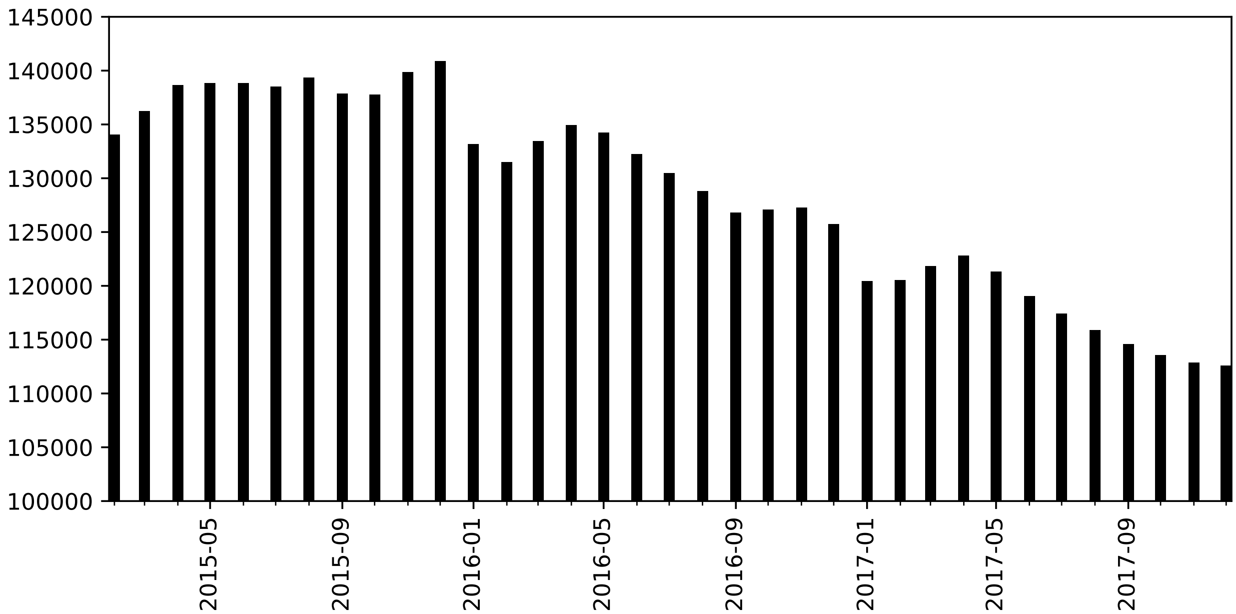
| | |
|---|---|
| **Count** | 20,459 |
| **Mean** | 1.04 |
| **Mode** | 1.00 |
| **Std** | 0.30 |
| **Min** | 0.40 |
| **Max** | 2.50 |
| **10%** | 0.72 |
| **25%** | 0.90 |
| **50%** | 1.00 |
| **75%** | 1.12 |
| **90%** | 1.41 |

**Note:** This table displays the distribution of the price ratio $\hat{P}_{ijt}$, derived from equations (12) and (13). I have excluded price ratios in the 1st and 99th percentile to mitigate the influence of extreme values. The descriptive statistics include the 10th percentile, 25th percentile, 50th percentile (i.e. the median), 75th percentile, and 90th percentile. These percentiles represent points in the distribution of the price ratio that divide the data into different segments. For example, the 25th percentile, also known as the first quartile, represents the value below which 25 percent of the data falls.

Consequently, the price evolution shown in Figure 6 warrants a cautious interpretation. While the Fisher index accounts for shifts in product sets and changing expenditure weights, it does not capture the effect of (direct) successions. Put in the context of the Brexit referendum period, it is likely that prices did not decrease as dramatically prior to the referendum and may have increased more significantly post-referendum than what Figure 6 indicates when taking direct successions into account.

Turning to Table 4, however, it can be observed that 20,459 price ratios were computed from February 2015 to December 2017. This translates to an average of 585 monthly price relatives that go unnoticed in standard matched price indices. As shown in Figure 8, the number of PRP transacted in two adjacent periods is significantly higher. I find a monthly average of 128,562 PRP that are transacted in two adjacent periods, which corresponds to the number of monthly price relatives that build the basis for a standard Fisher price index. This implies that only 1 out of 219 PRP undergoes a direct succession each month. This modest rate suggests that while there seem to be inflationary pressures from direct successions, their economic impact to the average consumer is rather limited.

Figure 8: Temporal evolution in the count of PRP in two adjacent periods in the reduced scanner dataset sample




**Note:** This figure illustrates the number of PRP that have records in both the current and previous month in the reduced scanner dataset sample.

The second dimension of the succession bias are volume-adjusted direct successions. Strategic decisions by manufacturers or retailers to reduce the size or quantity of a product over-proportionally compared to its price, effectively resulting in a hidden price increase, is often labelled as 'shrinkflation' (Bennett, 2022). This decision might not always be driven by production costs or consumer demand but can be a tactic to discreetly increase effective prices. The methodology to detect direct successors grouped products based on various characteristics, with packaging volume and size being crucial determinants. This grouping strategy allowed the use of unit values in the analysis. However, challenges arise when a new product enters the market that is nearly identical to an established one, but with distinct packaging dimensions. Such variations render the direct use of unit values inadequate. To address the potential impact of shrinkflation, I have revised the grouping strategy. PRP are now grouped based on previously defined characteristics, but with the omission of package volume/size. Consequently, I derive unit prices, or prices per unit volume (for example, price per millilitre or price per gram). For clarity, consider Table 3. Haribo products initially included in product groups 120980 and 121083 would now converge into a singular group, given that all defining characteristics, except for volume, are consistent across these products.[11]

To gauge the impact of volume-adjusted direct successions, I follow a similar approach as before. I compute the unit price ratio of a newly introduced PRP relative to the weighted average unit price of the established PRP in its group, as illustrated in equations (12) and (13). However, in this context, I utilize prices per unit volume instead of absolute prices, or unit values. The distribution of this resultant unit price ratio, denoted as $\hat{P}^U_{ijt}$, is shown in the left panel of Table 5.

Table 5: Distribution of the price ratios $\hat{P}^U_{ijt}$ and $\hat{P}^U_{igt}$

| | $\hat{P}^U_{ijt}$ | $\hat{P}^U_{igt}$ |
|---|---|---|
| **Count** | 44,313 | 88,714 |
| **Mean** | 1.13 | 1.33 |
| **Mode** | 1.00 | 1.00 |
| **Std** | 0.49 | 0.86 |
| **Min** | 0.30 | 0.21 |
| **Max** | 4.10 | 6.77 |
| **10%** | 0.65 | 0.55 |
| **25%** | 0.84 | 0.79 |
| **50%** | 1.00 | 1.11 |
| **75%** | 1.28 | 1.60 |
| **90%** | 1.71 | 2.32 |

**Note:** This table presents the distribution of unit price ratios, $\hat{P}^U_{ijt}$ and $\hat{P}^U_{igt}$, derived from equations (12) and (13) utilizing prices per unit volume instead of absolute prices. The left column illustrates the distribution of the unit price ratio for volume-adjusted direct successions, while the right column delineates the ratio for similar product successions. I have omitted unit price ratios in the 1st and 99th percentiles to curtail the effect of outliers.

The table shows that 44,313 unit price ratios were computed from February 2015 to December 2017, which corresponds to 1,266 monthly price relatives that go unnoticed in standard matched price indices. Consequently, for every 101 PRP, one experiences a volume-adjusted direct succession on a monthly level. Thus, while the mean of 1.13 implies inflationary effects from volume-adjusted direct successions, their economic impact remains relatively marginal.

The third facet of succession bias pertains to similar product successions. To identify these, I categorize products based on their association with a particular retailer and a narrowly defined product category. Referring to Table 3, Haribo products sold in retailer 111 would be grouped together with other products of the category 'Sugar Fruit Candies' sold in the same retailer.

To account for the impact of similar product successions, I create a unit price ratio of a newly introduced PRP and the weighted average unit price of established PRP within its group, as outlined in equations (12) and (13). I again use prices per unit volume, but now apply granular categories as groups. This method is applied to all new PRP for which a price ratio, based on volume-adjusted direct successions, could not be established. Consequently, the price ratio for all newly introduced successor products with a near-perfect substitute are integrated into the distribution displayed in the left panel of Table 5, while being omitted from the computation of price ratios for similar product successions. The distribution of this resultant unit price

[11] It is important to note that shrinkflation cannot occur within an unchanged product id as any modification in volume mandates the assignment of a new product id. Accordingly, shrinkflation can be viewed as one dimension of product succession.

ratio, denoted as $\hat{P}^U_{igt}$, can be found in the right panel of Table 5. It is important to highlight that in contrast to the previous unit price ratio $\hat{P}^U_{ijt}$, the product group $j$ is now substituted by category $g$.

From February 2015 to December 2017, I computed 88,714 unit price ratios for similar product successions. This equates to a monthly average of 2,535 price relatives, signifying that every month, 1 in 50 PRP undergoes a similar product succession. The average value of 1.33 suggests that newly introduced successor products, even in the absence of a near-perfect substitute but in the presence of highly analogous products, exert an inflationary impact.

When I factor in volume-adjusted direct successions, the numbers reveal an average of 3,801 monthly price relatives that are overlooked in standard matched price index methods. This means that each month, 1 out of every 34 PRP experiences a succession. Given these figures, the inflationary economic impact on the average consumer may indeed be more significant than previously assumed.

To investigate if the Brexit referendum marks a significant shift in inflationary effects from product succession, I employ a simple regression model. The dependent variable is the unit price ratio $\hat{P}^U_{ijt}$. However, there are PRP introductions where $\hat{P}^U_{ijt}$ is not available. In such cases, I substitute it with the unit price ratio $\hat{P}^U_{igt}$, serving as a suitable alternative for the analysis. The independent variables include month dummies, category fixed effects, and a post-Brexit referendum dummy. The model can formally be expressed as:

$$Y = \beta_0 + \sum_{m=1}^{11} \delta_m Month_{mt} + \sum_{c=1}^{C} \gamma_c Category_{ct} + \beta_1 Brexit_t + \epsilon_{it} \tag{14}$$

where $Y$ is the dependent variable which takes the value of $\hat{P}^U_{ijt}$ if it is available, otherwise it takes the value of $\hat{P}^U_{igt}$. As defined above, $\hat{P}^U_{ijt}$ is the unit price ratio for a PRP $i$ in product group $j$ at time $t$ and $\hat{P}^U_{igt}$ is the unit price ratio for a PRP $i$ in category $g$ at time $t$. $Month_{mt}$ are the month dummies (January is considered as the base and thus excluded), $Category_{ct}$ are the category fixed effects (with $C = 1171 - 1$ granular categories), $Brexit_t$ is a binary variable indicating the post-Brexit period starting from June 2016 and $\epsilon_{it}$ is the error term. The coefficient $\beta_1$ captures systematic differences in the price ratio after the Brexit referendum, while accounting for the temporal and category-based effects.

The regression results are presented in Table 6. The coefficient on the constant is 1.188 and significantly different from 1 at all conventional significance levels.[12] This implies that, when all other predictors in the model are set to zero (i.e., considering the reference category for January and Brexit referendum not having occurred), the projected value of the price ratio is 1.188. The coefficients on the months February, November and December are positive and highly significant, indicating that the inflationary impact stemming from successions is stronger in those months as compared to January. This aligns with the previous observation that price movements are subject to seasonal patterns, with prices always exhibiting a surge at the end of a year, followed by a drop in January (see, e.g., Figure 3). More importantly, the Brexit variable has a

[12] This estimated value is significantly different from 0 at conventional significance levels, as indicated by its p-value. Based on the 95 percent confidence interval, which ranges from 1.162 to 1.214, this coefficient is also significantly different from 1 at the 5 percent significance level. Extending the significance criterion, even at the 1 percent level, the coefficient remains significantly different from 1.

coefficient of 0.037. This suggests that, after accounting for monthly variations and categories, there was an average increase in the price ratio of 0.037 units post-Brexit referendum compared to the period before. This effect is statistically significant at the 1 percent level, implying that the Brexit vote has had a measurable impact on the price ratio. As an example, if the price ratio was 1.00 before Brexit for a specific PRP in a particular category and month, then after Brexit, the price ratio would increase by 0.037, leading to a new price ratio of 1.037, which would imply a 3.7 percent increase in the price ratio post-Brexit compared to the period before, i.e. successions-based inflation accelerated post-referendum.[13] It is essential to recognize the cumulative significance of this coefficient. Given that the 0.037 applies each month, this translates to substantial price shifts over a year or more. For instance, over a 12-month period post-Brexit, this monthly increment could compound to a considerable change in the price ratio, underscoring the profound impact of the Brexit vote on pricing dynamics via product successions.

Table 6: Effects of the Brexit vote on $\hat{P}^U_{ijt}$ and $\hat{P}^U_{igt}$: Regression results

| | coef | std err | t | p | 0.025 | 0.975 |
|---|---|---|---|---|---|---|
| **Constant** | 1.188*** | 0.013 | 89.26 | 0.000 | 1.162 | 1.214 |
| **Brexit** | 0.037*** | 0.008 | 4.375 | 0.000 | 0.02 | 0.054 |
| **Feb** | 0.053*** | 0.017 | 3.109 | 0.002 | 0.019 | 0.086 |
| **Mar** | 0.012 | 0.016 | 0.762 | 0.446 | -0.02 | 0.044 |
| **Apr** | 0.016 | 0.016 | 0.974 | 0.33 | -0.016 | 0.047 |
| **May** | 0.014 | 0.015 | 0.966 | 0.334 | -0.015 | 0.044 |
| **Jun** | 0.001 | 0.015 | 0.093 | 0.926 | -0.028 | 0.031 |
| **Jul** | 0.008 | 0.016 | 0.528 | 0.598 | -0.022 | 0.039 |
| **Aug** | 0.030* | 0.017 | 1.815 | 0.07 | -0.002 | 0.063 |
| **Sep** | 0.026* | 0.015 | 1.704 | 0.089 | -0.004 | 0.057 |
| **Oct** | 0.031** | 0.016 | 1.969 | 0.049 | 0.000 | 0.062 |
| **Nov** | 0.072*** | 0.021 | 3.386 | 0.001 | 0.03 | 0.113 |
| **Dec** | 0.098*** | 0.019 | 5.015 | 0.000 | 0.059 | 0.136 |
| **[Categories not shown]** | | | | | | |
| **No. obs** | 133,027 | | | | | |
| **Degrees of freedom** | 131,844 | | | | | |
| **No. categories** | 1,171 | | | | | |
| **Adj. R-squared** | 0.057 | | | | | |
| **Standard Errors are robust to cluster correlation at the category level** | | | | | | |
| ***p<0.1 **p<0.05 ***p<0.01** | | | | | | |

**Note:** This table displays regression outcomes from equation (14). Category statistics are omitted for visibility. Standard errors are clustered at the category level. The columns '0.025' and '0.975' refer to the lower and upper bounds of the 95 percent confidence interval, respectively. The number of observations coincide with the sum of the count row in Table 5.

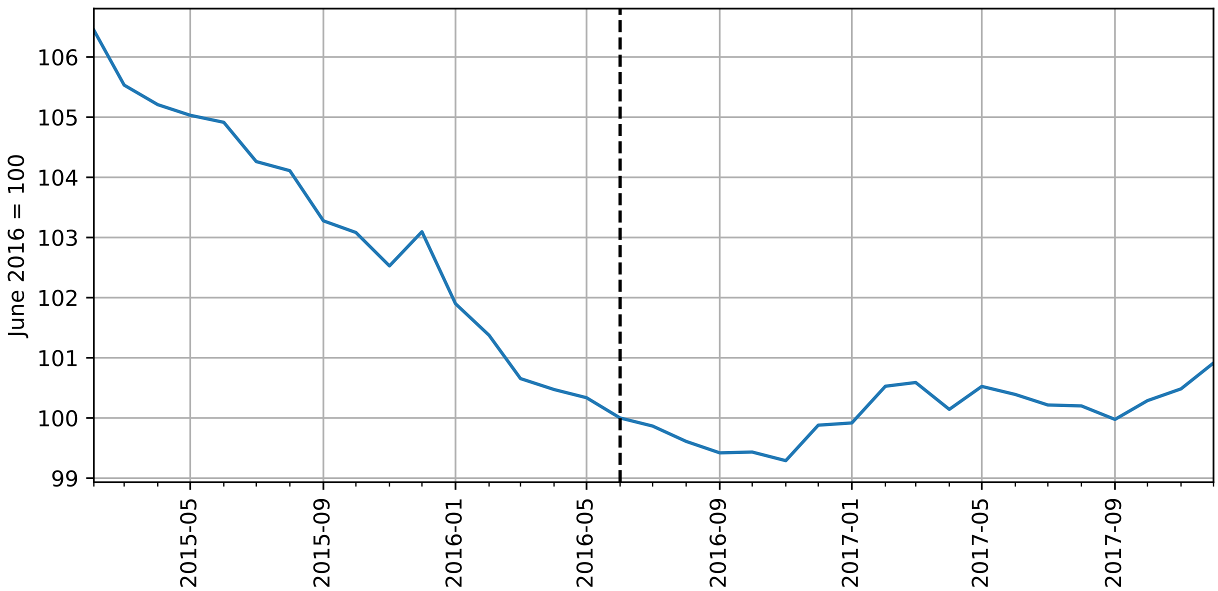
Having demonstrated that successions exert an inflationary impact and occur with notable frequency, it is crucial to quantify the extent of this 'succession bias' on the overall price evolution. To do so, I compute a Fisher price index that overlooks successions (baseline Fisher price index), and compare it to a Fisher price index that integrates the price relatives at the point of successor introductions, i.e. at the onset of their successions (successions-adjusted Fisher price index).

I calculate the baseline Fisher price index using equations (6) through (11). Notably, the price relatives, $R_{it}$, are now defined as unit price relatives. This adaptation leads to a slightly more restrictive representative sample of PRP, $\Omega_t$, refreshed every month. Specifically, I have excluded products measured in 'Pieces', those lacking a brand name, and those that either do not provide volume information or offer ambiguous

[13] If the price ratio was higher than 1 before Brexit for a specific PRP in a particular category and month, then after Brexit, the price ratio would increase by 0.037, which amounts to a less than one-to-one percent increase. If the price ratio was lower than 1 before Brexit for a specific PRP in a particular category and month, then after Brexit, the price ratio would increase by 0.037, which amounts to a more than one-to-one percent increase. At the 25th percentile (see Table 5), the percent increase would amount to 0.037/0.84*100=4.4 and 0.037/0.79*100=4.7, respectively. At the 75th percentile, the percent increase would amount to 0.037/1.28*100=2.9 and 0.037/1.60*100=2.3, respectively.

volume descriptions (as explained before). The temporal evolution of the refined representative sample, $\Omega_t$, is depicted in Figure 8. Meanwhile, Figure 9 presents the baseline Fisher unit price index derived from this sample. Notably, the Fisher unit price index derived from the narrowed scanner data sample aligns closely with the Fisher price index derived from the complete scanner data set, as depicted in Figure 6.

Figure 9: Evolution of the FMCG Fisher unit price index (dynamic basket)



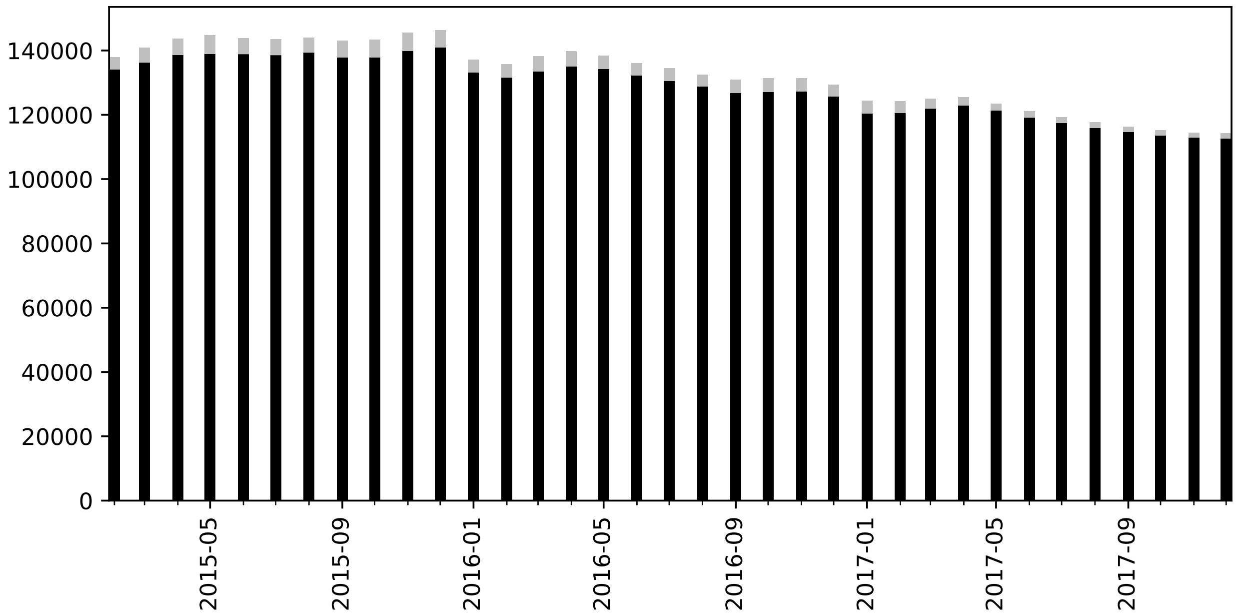

**Note:** This figure illustrates the FMCG Fisher unit price index, which is computed based on a sub-sample of PRP $\Omega_t$ that is refreshed in each month $t$ as shown in Figure 8. The value of the index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure.

The successions-adjusted Fisher price index builds upon the baseline approach with a crucial modification: I incorporate the price relatives of successions as detailed in Table 5 at their respective introduction months. The representative sample of PRP, $\Omega_t$, reflecting these adjustments is illustrated in Figure 10. As previously described, a succession occurs on average for every 34th PRP on a monthly basis. As a result, the grey region, representing the price relatives of these successions, is discernible but remains relatively subtle in its presence. Consistent with this observation, the monthly expenditure change due to the incorporation of successors, as illustrated in Figure 11, reveals that they command a modest market share.

In both the baseline and successions-adjusted Fisher price indices, the Laspeyres-type indices remain consistent, given that previous period weights of new product introductions are zero. However, their Paasche-type counterparts differ due to observable current period weights for these newly introduced successors. Thus, a potential divergence between the baseline and the successions-adjusted Fisher price indices can be attributed to two reasons. First, newly introduced successors capturing a significant portion of total expenditure in their introduction month. However, this scenario is negated by the data shown in Figures 10 and 11. The second potential factor is the consistent inflationary effect of successions, which is evidenced in Table 5.

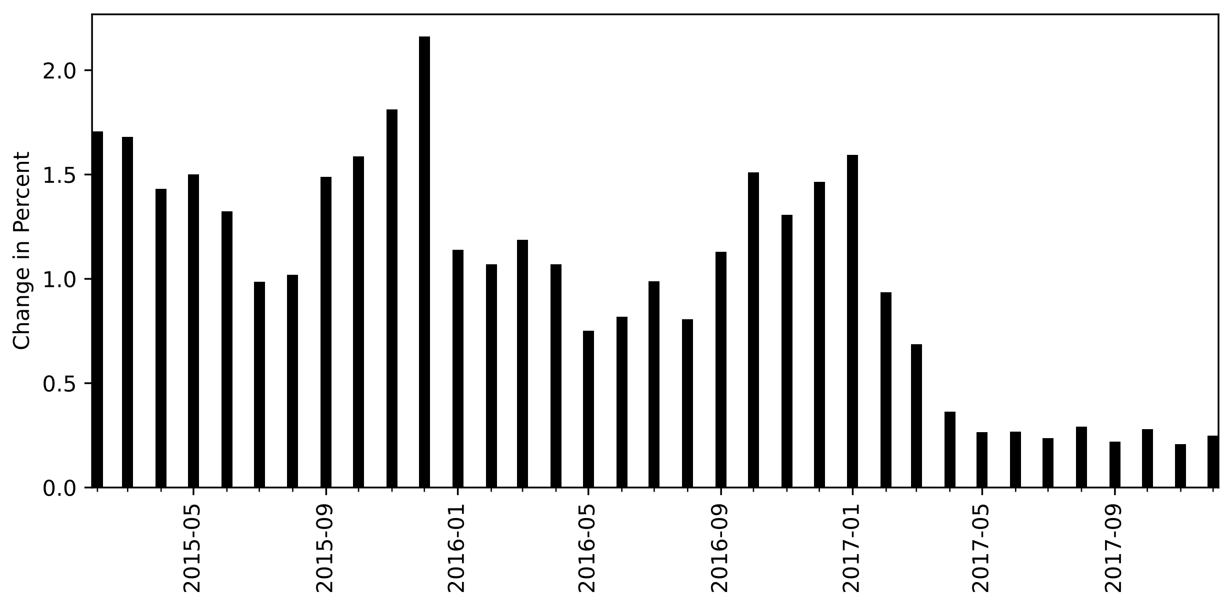
The side-by-side comparison of the successions-adjusted and the baseline Fisher price indices is displayed

Figure 10: Temporal evolution in the count of PRP in two adjacent periods (+ newly introduced PRP) in the reduced scanner dataset sample




**Note:** This figure illustrates the number of PRP observed in two adjacent periods. The shaded region represents newly introduced PRP, i.e. for those PRP I do not directly observe prices in the preceding period, but I computed them.

Figure 11: Temporal evolution of expenditure change: Impact of newly introduced PRP




**Note:** This figure shows the change in expenditure resulting from the introduction of PRP.

in Figure 12. The observed differences suggest that, when accounting for successions, prices did not drop as steeply before the referendum and rose more sharply after it. This underlines the importance of the inflationary impact of successions, even if their frequency is relatively low.

Figure 12: Evolution of the FMCG Fisher unit price index (dynamic basket): Baseline and successions-adjusted


**Note:** This figure illustrates the FMCG Fisher unit price indices, baseline and successions-adjusted. The value of the index is normalized to 100 in June 2016, the referendum month, represented by a vertical line in the figure.

To analyze the implications of complete external margin effects on price evolution, I undertake an expanded analysis that factors in re-appearing products alongside newly introduced successor products. Rather than focusing solely on the succession bias, the emphasis shifts to understanding the overall extensive margin bias that is often overlooked in conventional price indices. For a clearer understanding, consider the following example: A product makes its first appearance in November 2015, remaining available for five consecutive months until March 2016. It then temporarily exits the market in April, returns in May, disappears once again, only to make a comeback from November 2016 through to March 2017. Using this timeline, direct price relatives can be derived from December 2015 to March 2016 and from December 2016 to March 2017.

However, there is another dimension to consider: The price relatives in relation to near-perfect substitutes or highly analogous products. These can be computed for three specific moments. First, November 2015, when the product is newly introduced. Second, May 2016, during its first re-entry. Third, November 2016, during its second comeback. In my previous methodology, I restricted the analysis to price relatives exclusively in relation to near-perfect substitutes or similar products when a product was being introduced for the very first time. However, in this broader analysis, I encompass the computed price relatives for moments when products re-emerge in the market. In doing so, I touch upon the entirety of the extensive margin bias inherent in standard price indices by considering every conceivable price relative that cannot be determined directly.

In the expanded approach, I develop a unit price ratio for PRP that are either newly introduced or reenter the market. This ratio juxtaposes the unit price of such PRP with the weighted average unit price of their established counterparts within the same group. I derive this method from the previously mentioned equations (12) and (13), utilizing prices per unit volume. This new unit price ratio is represented as $\tilde{P}^U_{ijt}$. However, there are instances where a direct price ratio, based on volume-adjusted direct substitutes, is not feasible for these newly-introduced or re-appearing products. In these cases, I construct a unit price ratio by leveraging the weighted average unit price of established products within the same category. This alternative ratio is denoted as $\tilde{P}^U_{igt}$. To further elaborate: All newly-introduced or re-appearing PRP that possess a near-perfect substitute will have their price ratio incorporated into the left panel of Table 7. These particular PRP are then excluded when computing the price ratios of PRP with similar attributes, which are shown in the right panel of the same table. In both cases, the mean exceeds 1, indicating that when newly-introduced or re-emerging PRP enter the market, they do so at a unit price higher than that of their near-perfect substitutes or closely related PRP. Additionally, the substantial number of computed price ratios underscores that the temporary absence of products and the prevalence of rapidly shifting purchasing patterns are inherent traits of this market.

Table 7: Distribution of the price ratios $\tilde{P}^U_{ijt}$ and $\tilde{P}^U_{igt}$

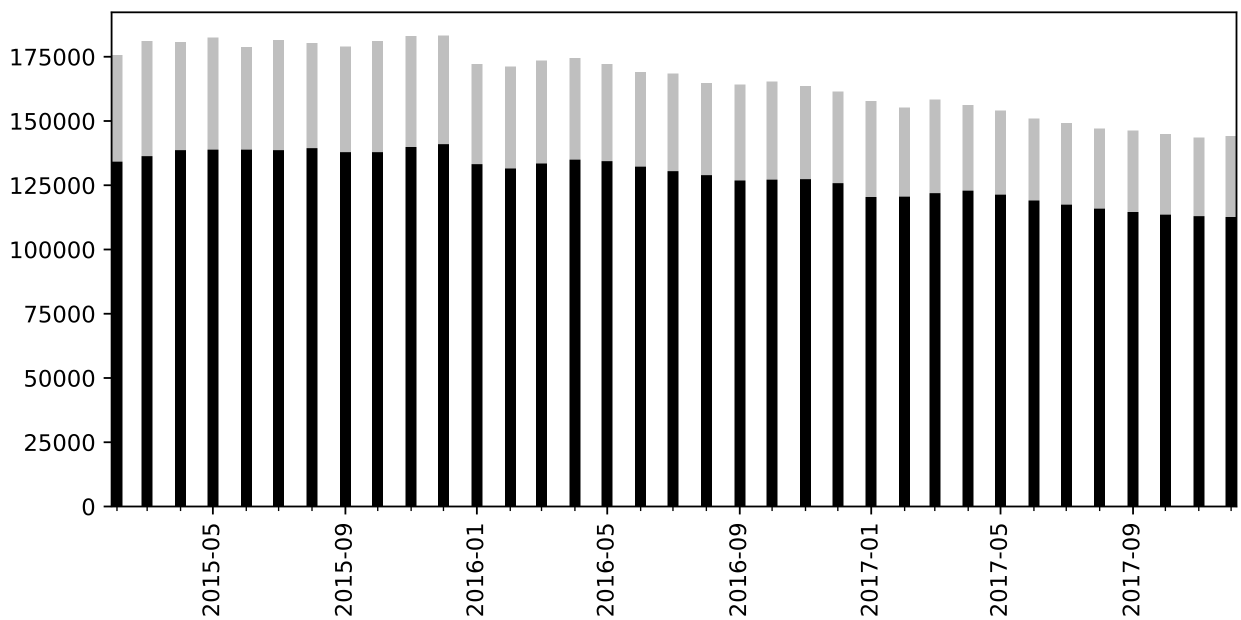
| | $\tilde{P}^U_{ijt}$ | $\tilde{P}^U_{igt}$ |
|---|---|---|
| **Count** | 540,205 | 774,436 |
| **Mean** | 1.10 | 1.27 |
| **Mode** | 1.00 | 1.00 |
| **Std** | 0.47 | 0.80 |
| **Min** | 0.29 | 0.20 |
| **Max** | 4.00 | 6.31 |
| **10%** | 0.65 | 0.53 |
| **25%** | 0.83 | 0.76 |
| **50%** | 1.00 | 1.07 |
| **75%** | 1.24 | 1.52 |
| **90%** | 1.63 | 2.19 |

**Note:** This table displays the distribution of the unit price ratio $\tilde{P}^U_{ijt}$ and $\tilde{P}^U_{igt}$. The left column captures the distribution of the unit price ratio based on volume-adjusted newly-introduced or re-appearing products, whereas the right column focuses on the unit price ratio of based on the similar products definition. I have excluded unit price ratios in the 1st and 99th percentile to mitigate the influence of extreme values.

The extended analysis incorporates an adjusted sample of PRP, which accounts for the extensive margin. The month-to-month representation of this adjusted sample is shown in Figure 13. Notably, PRP that are either newly introduced to the market or make a re-appearance constitute approximately one fifth of the total PRP each month. To gain a more comprehensive understanding of the market dynamics, I also provide an insight into the monthly expenditure patterns. Specifically, the change of total spending due to PRP that have been either newly introduced or have re-entered the market is illustrated in Figure 14. This expenditure change consistently remains in the range of approximately 4-7 percent, signifying its substantial impact on the overall market dynamics, especially in light of the inflationary effects of extensive margin adjustments as revealed in Table 7. To visualize the effects on the overall price evolution, Figure 15 juxtaposes the three different indices: the baseline Fisher unit price index, the successions-adjusted Fisher unit price index, and the newly created extensive margin-adjusted Fisher unit price index. The last index indicates a pronounced price surge post-referendum, and a modest decline preceding it. The divergence between these series is compelling, emphasizing the necessity of factoring in extensive margin adjustments in the construction of price indices.

Furthermore, a comparison with Figure 3 illustrates a divergence between price indices derived from the full utilization of information included in scanner data and those that selectively use a subset of this information, mimicking the methods implemented in the computation of official inflation numbers. This discrepancy, coupled with the theoretical advantages of employing scanner data as highlighted in Dubois & Griffith & O'Connell (2022), speaks in favor of the integration of scanner data into the computation of official inflation statistics.

Figure 13: Temporal evolution in the count of PRP in two adjacent periods (+ newly introduced PRP and re-appearing PRP) in the reduced scanner dataset sample



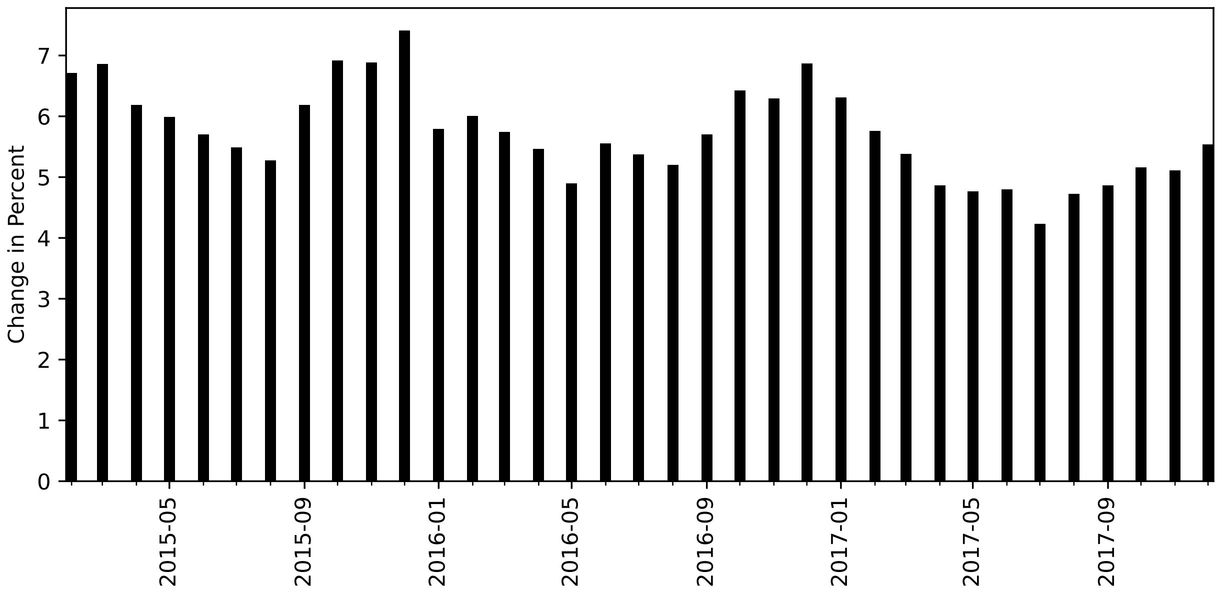

**Note:** This figure illustrates the number of PRP observed in two adjacent periods. The shaded region represents both newly introduced PRP and those that re-appeared, i.e. for those PRP I do not directly observe prices in the preceding period, but I computed them.

Finally, I revisit the regression detailed in equation (14), with a singular adjustment: Now, the dependent variable $Y$ takes the value of $\tilde{P}^U_{ijt}$ if it is available, otherwise it takes the value of $\tilde{P}^U_{igt}$. The outcomes of this regression can be found in Table 8. These results reinforce the earlier observation, indicating a pronounced positive influence of the Brexit vote on the price ratio. To put it differently: Inflation driven by extensive margin adjustments accelerated post-referendum.

## 3.4. Price dynamics of imported and domestic products

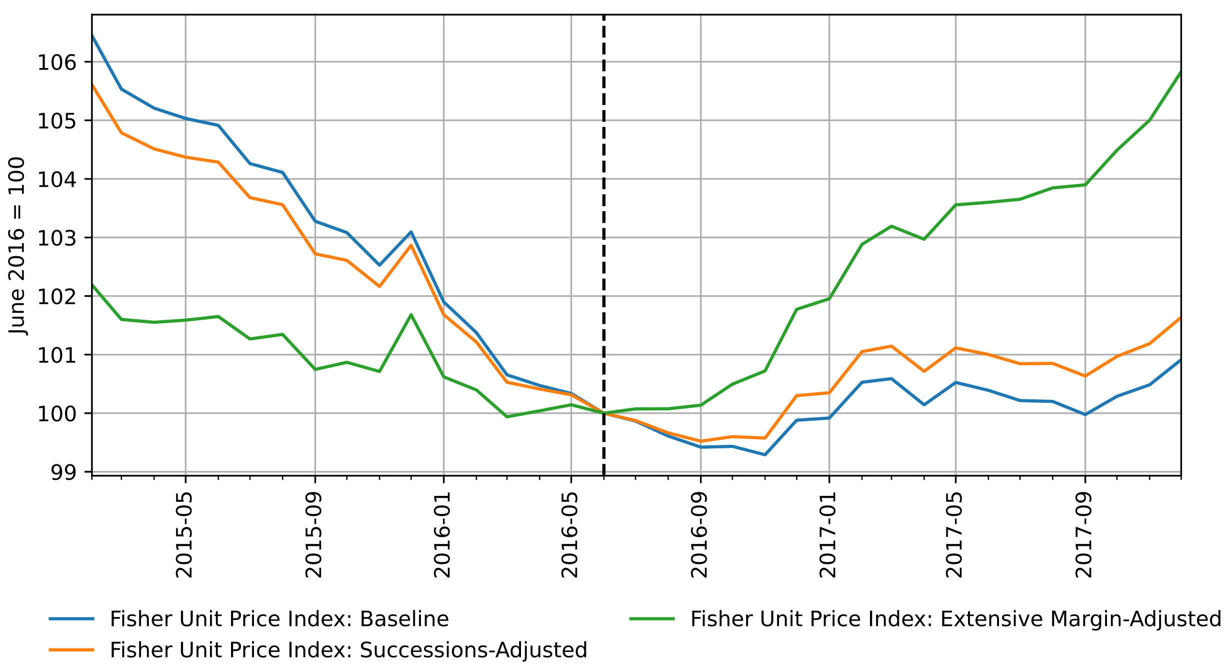
In the period leading up to and following the Brexit referendum, the Pound sterling witnessed a pronounced depreciation, as illustrated in Figure 1. Such an evolution brings forth the question of the price impact on products produced abroad and imported to the domestic economy (foreign products). Due to their direct

Figure 14: Temporal evolution of expenditure change: Impact of newly introduced and re-appearing PRP




**Note:** This figure shows the change in expenditure resulting from the introduction and re-appearance of PRP.

Figure 15: Evolution of the FMCG Fisher unit price index (dynamic basket): Baseline, successions-adjusted and extensive margin-adjusted




**Note:** This figure plots the three different Fisher unit price indices: baseline, successions-adjusted, and extensive margin-adjusted.

linkage with exchange rate fluctuations, foreign products are usually assumed to be inherently more sensitive to currency devaluations than domestically produced products (domestic products). As such, one might

Table 8: Effects of the Brexit vote on $\tilde{P}^U_{ijt}$ and $\tilde{P}^U_{igt}$: Regression results

| | coef | std err | t | p | 0.025 | 0.975 |
|---|---|---|---|---|---|---|
| Constant | 1.057*** | 0.005 | 226.871 | 0.000 | 1.048 | 1.066 |
| Brexit | 0.010*** | 0.002 | 4.495 | 0.000 | 0.006 | 0.015 |
| Feb | 0.037*** | 0.006 | 6.314 | 0.000 | 0.025 | 0.048 |
| Mar | 0.027*** | 0.005 | 5.192 | 0.000 | 0.017 | 0.038 |
| Apr | 0.027*** | 0.005 | 5.173 | 0.000 | 0.017 | 0.037 |
| May | 0.025*** | 0.005 | 4.681 | 0.000 | 0.014 | 0.035 |
| Jun | 0.024*** | 0.005 | 4.381 | 0.000 | 0.013 | 0.035 |
| Jul | 0.025*** | 0.005 | 4.843 | 0.000 | 0.015 | 0.035 |
| Aug | 0.022*** | 0.005 | 4.141 | 0.000 | 0.011 | 0.032 |
| Sep | 0.024*** | 0.005 | 4.616 | 0.000 | 0.014 | 0.034 |
| Oct | 0.030*** | 0.006 | 4.996 | 0.000 | 0.018 | 0.042 |
| Nov | 0.046*** | 0.007 | 6.353 | 0.000 | 0.032 | 0.060 |
| Dec | 0.049*** | 0.006 | 7.988 | 0.000 | 0.037 | 0.061 |
| [Categories not shown] | | | | | | |
| No. obs | 1,314,641 | | | | | |
| Degrees of freedom | 1,313,294 | | | | | |
| No. categories | 1,335 | | | | | |
| Adj. R-squared | 0.027 | | | | | |
| Standard Errors are robust to cluster correlation at the category level | | | | | | |

**Note:** This table displays regression outcomes from equation (14) adjusted to take $\tilde{P}^U_{ijt}$ and $\tilde{P}^U_{igt}$ into account as dependent variables. Category statistics are omitted for visibility. Standard errors are clustered at the category level. The columns '0.025' and '0.975' refer to the lower and upper bounds of the 95 percent confidence interval, respectively. The number of observations coincide with the sum of the count row in Table 7.

anticipate that the inflationary effects brought on by exchange rate dynamics would predominantly manifest in the pricing of foreign products. This phenomenon is reflected in numerous structural macroeconomic models, including those by Obstfeld & Rogoff (1995), Corsetti & Dedola & Leduc (2008), Burstein & Gopinath (2014), and Dieppe et al. (2018).

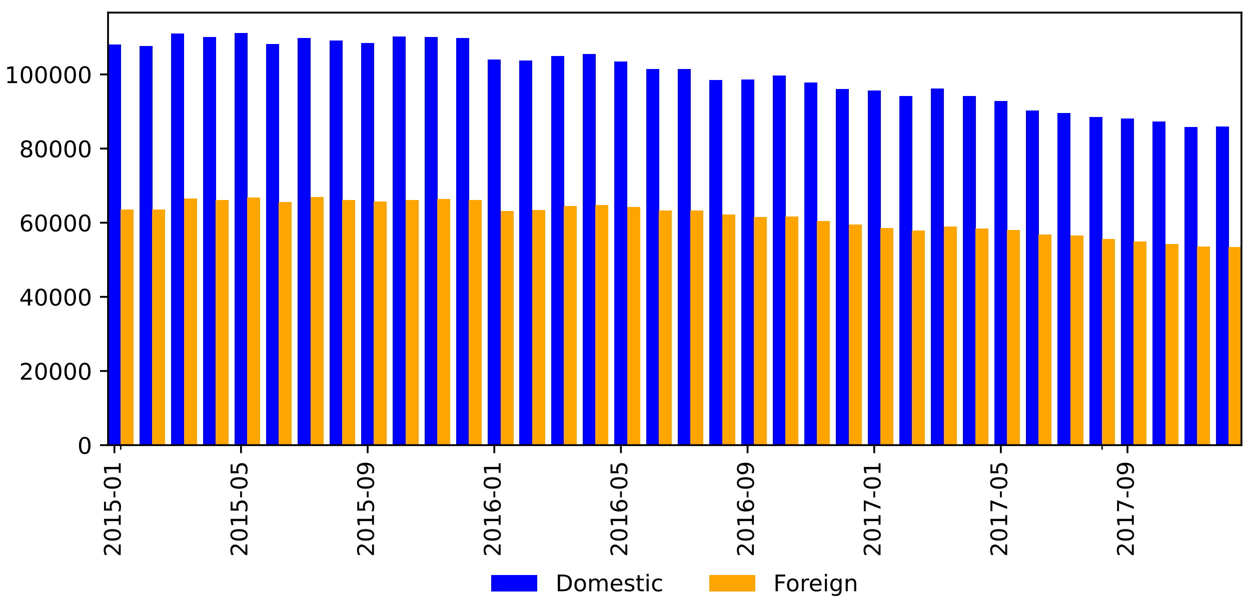
However, a nuanced consideration of global and local distribution markets reveals that products are strongly interlinked. Even as consumers directly purchase foreign products, they are also indirectly engaged in the consumption of imports when opting for domestic products. This is due to the incorporation of imported inputs in the production processes of many domestic products. While this indirect channel does imply that domestic products could potentially face upward price pressures around the time of the Brexit referendum, the degree and timing of this effect is likely subdued compared to the direct price hikes experienced by foreign products. This hypothesis is in line with the implications from several structural macroeconomic models (as outlined above), in which a depreciating domestic currency directly influences aggregate consumer prices by driving up prices of imported products and thus the overall price level. Simultaneously, an indirect effect comes into play, where domestically produced products also experience a rise in prices. This can be attributed to an increase in the costs of foreign intermediate inputs, or a demand shift favouring domestic products. Consequently, while aggregate consumer prices are unambiguously on the rise, it can also be inferred from those models that prices of imported products increase more strongly than prices of domestically produced products. The extent of these relative price fluctuations, however, hinges on a variety of factors, necessitating an empirical approach for accurate assessment.

Moreover, the local distribution sector (e.g., wholesalers, distributors and retailers) may be willing to accept a lower markup for foreign products following a product-specific cost increase, which they eventually compensate by increasing the prices of both foreign and domestic products. Similarly, local costs involved in bringing the products to the shelves, which are likely unaffected by fluctuations in the exchange rate, might drive a wedge between price changes at the border and the retail level.

In light of the complex interplay between the depreciating Pound sterling, global networks, and local distribution structures, both foreign and domestic products may have been subjected to inflationary pressures in the period surrounding the Brexit referendum. Although the sharp devaluation of the Pound sterling might lead one to expect pronounced differences in how these pressures manifest across products based on their origin, the reality could be more complex. Within this section, the aim is to empirically dissect this distinction, delving into the differential price movements of foreign and domestic products against the backdrop of a significant exchange rate depreciation.[14]

A major strength of the dataset is its ability to differentiate between foreign and domestic products.[15] Following Bems & Giovanni (2016), I identify the foreign/domestic origin of each product via barcode characteristics. In particular, the first three digits of the Global Trade Identification Number (GTIN) identify the country in which the label was applied for. Figure 16 presents the count of both foreign and domestic PRP within the reduced scanner dataset sample.[16]

Figure 16: Temporal evolution in the count of foreign and domestic PRP




**Note:** This figure depicts the counts of foreign and domestic PRP used in the analysis over the specified time period.

I first assess the relative prices of foreign products compared to their domestic counterparts. To shed light on this, I compute log unit price ratios of foreign products relative to domestic ones, keeping the category,

[14]While this analysis offers empirical insights, I neither aim to pin down nor theorize the exact mechanisms at play.

[15]I am aware of the fact that differentiating between foreign and domestic products, especially in today's era of global supply chains, can be complicated. For instance, a product could be designed in one country, manufactured in another, and assembled in a third. Moreover, the origin of products can change over time. For instance, a product previously imported might start being produced domestically or vice versa. Nevertheless, I believe this approach provides a pragmatic way to categorize products based on their predominant origin. Given the vast complexities of the modern supply chain, achieving a perfect delineation between foreign and domestic products would require granular data at every stage of a product's lifecycle, which is often impractical or unavailable. Thus, while the categorization may not be perfect, it represents a significant step forward in understanding the dynamics of foreign versus domestic products in the context of pivotal events like the Brexit referendum.

[16]I had to drop approximately 5 percent of products for which I could not identify the origin, as the barcode does not coincide with the typical GTIN structure.

retailer, and month consistent. As an example, such a log unit price ratio would reveal whether foreign variants of products, be it 'Sugar Fruit Candies', 'Ready To Eat Cereals', etc., sold by a particular retailer, tend to be pricier than their domestic counterparts. This analysis is based on the following equation:

$$\ddot{P}_{gt}^{U} = \ln\left(\frac{GM_{gt}^{U,F}}{GM_{gt}^{U,D}}\right) \tag{15}$$

where $GM_{gt}^{U,O}$ represents the weighted geometric mean of unit prices for category $g$ and origin $O$, where $O$ can be either domestic or foreign, in period $t$.

The formula for calculating the weighted geometric mean of unit prices is:

$$GM_{gt}^{U,O} = \prod_{i \in g_t^O} {P_{it}^{U}}^{w_{it}} \tag{16}$$

In this equation, $P_{it}^{U}$ denotes the unit price of PRP $i$ in period t, while $w_{it}$ is the proportion of total expenditure on PRP $i$ of origin $O$ during period $t$ to the cumulative expenditure on all products in category $g$ of the same origin during the same period.

The distribution of the log unit price ratio $\ddot{P}_{gt}^{U}$ is depicted in Table 9. A mean value that is negative suggests that, on average, domestic PRP are priced higher than their foreign counterparts. To be specific, the mean value of -0.09 in the log unit price ratio translates to domestic PRP being approximately 9 percent more expensive than foreign products, when considering products in the same category, sold by the same retailer within the same month.

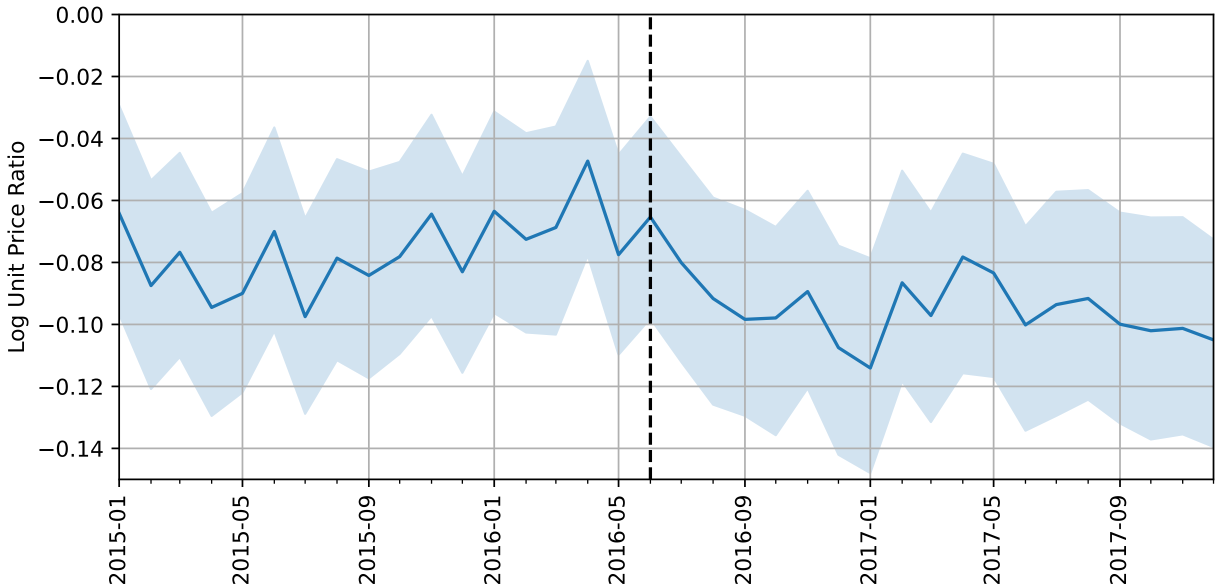
To assess how the mean evolves over time and whether it is statistically significantly different from zero, I plot the mean for each month alongside its 95 percent confidence interval in Figure 17. Notably, the entire 95 percent confidence interval is consistently below zero. This implies that, at a 5 percent significance level, the mean of $\ddot{P}_{gt}^{U}$ is statistically different from zero. What strikes the eye is that the mean of $\ddot{P}_{gt}^{U}$ becomes even more negative around the Brexit referendum period. This suggests a widening price differential: Domestic PRP enhanced their price premium relative to foreign PRP around the time of the Brexit referendum.

Table 9: Distribution of the unit price ratio $\ddot{P}_{gt}^{U}$

| | |
|---|---|
| **Count** | 285,872 |
| **Mean** | -0.09 |
| **Mode** | 0.00 |
| **Std** | 1.51 |
| **Min** | -7.06 |
| **Max** | 6.77 |
| **10%** | -1.23 |
| **25%** | -0.46 |
| **50%** | 0.00 |
| **75%** | 0.41 |
| **90%** | 0.99 |

**Note:** This table presents the distribution statistics for the log unit price ratio $\ddot{P}_{gt}^{U}$, as formulated in equations (15) and (16). Price ratios from the 1st and 99th percentiles have been excluded to minimize the impact of outliers.

Figure 17: Time series of the mean of unit price ratio $\ddot{P}^U_{gt}$




**Note:** This figure presents the time series evolution of the mean unit price ratio $\ddot{P}^U_{gt}$. The shaded region represents the 95 percent confidence interval around the mean.

To test whether the Brexit referendum marks a significant shift in $\ddot{P}^U_{gt}$, I estimate the following equation:

$$\ddot{P}^U_{gt} = \beta_0 + \sum_{m=1}^{11} \delta_m Month_{mt} + \sum_{c=1}^{C} \gamma_c Category_{ct} + \beta_1 Brexit_t + \epsilon_{gt} \tag{17}$$

where the dependent variable $\ddot{P}^U_{gt}$, derived from equations (15) and (16), represents the unit price ratio of imported PRP relative to domestic PRP for each category-retailer combination in month $t$. $Month_{mt}$ comprises month-specific dummy variables to control for monthly fixed effects (January is considered as the base and thus excluded), $Category_{ct}$ are the category fixed effects (with $C = 1083 - 1$ granular categories), $Brexit_t$ is a binary variable indicating the post-Brexit period starting from June 2016 and $\epsilon_{gt}$ is the error term. The coefficient $\beta_1$ captures systematic differences in the unit price ratio after the Brexit referendum, while accounting for the temporal and category-based effects.

The regression results are presented in Table 10. The Brexit coefficient is negative and statistically significant at the 5 percent significance level. This implies that, after the Brexit referendum, there is a statistically significant decrease in the unit price ratio of highly analogous foreign PRP relative to domestic ones, controlling for temporal and category-specific variations. In other words, foreign PRP are relatively cheaper or domestic PRP are relatively pricier in the aftermath of the Brexit referendum compared to the period before. The coefficient value of -0.013 suggests that, after the Brexit referendum, there was an average decrease in the unit price ratio of approximately 1.3 percent relative to the period before. From a consumer's perspective, this suggests a shift in the relative attractiveness of foreign products. Such a shift could potentially steer consumers away from domestic products towards foreign products.

Table 10: Effects of the Brexit vote on the unit price ratio $\ddot{P}^{U}_{gt}$: Regression results

| | coef | std err | t | p | 0.025 | 0.975 |
|---|---|---|---|---|---|---|
| Constant | -0.313*** | 0.077 | -4.074 | 0 | -0.463 | -0.162 |
| Brexit | -0.013** | 0.005 | -2.591 | 0.01 | -0.023 | -0.003 |
| Feb | -0.002 | 0.012 | -0.142 | 0.887 | -0.025 | 0.021 |
| Mar | 0.007 | 0.012 | 0.586 | 0.558 | -0.016 | 0.03 |
| Apr | 0.008 | 0.012 | 0.703 | 0.482 | -0.015 | 0.031 |
| May | -0.001 | 0.012 | -0.124 | 0.901 | -0.024 | 0.021 |
| Jun | 0.003 | 0.012 | 0.259 | 0.795 | -0.02 | 0.026 |
| Jul | -0.002 | 0.012 | -0.191 | 0.849 | -0.025 | 0.021 |
| Aug | -0.003 | 0.012 | -0.218 | 0.827 | -0.026 | 0.021 |
| Sep | -0.006 | 0.012 | -0.52 | 0.603 | -0.029 | 0.017 |
| Oct | -0.001 | 0.012 | -0.04 | 0.968 | -0.024 | 0.023 |
| Nov | -0.001 | 0.012 | -0.042 | 0.967 | -0.024 | 0.023 |
| Dec | -0.003 | 0.012 | -0.263 | 0.792 | -0.026 | 0.02 |
| [Categories not shown] | | | | | | |
| No. obs | 285,872 | | | | | |
| Degrees of freedom | 284,700 | | | | | |
| No. categories | 1,083 | | | | | |
| Adj. R-squared | 0.29 | | | | | |
| *p<0.1 **p<0.05 ***p<0.01 | | | | | | |

**Note:** This table displays regression outcomes from equation (17). Category statistics are omitted for visibility. The columns '0.025' and '0.975' refer to the lower and upper bounds of the 95 percent confidence interval, respectively. The number of observations coincide with the count in Table 9. Compared to Tables 6 and 8, standard errors are not clustered at the category level. This is because each observation is already an aggregate of a category, and that clustering on that level would be redundant. If I cluster standard errors on the retailer level, the Brexit coefficient is unaffected, but the p-value increases to 0.118.

The former results suggest that prices of foreign products did not increase stronger than prices of domestic products around the time of the Brexit referendum. However, before drawing definitive conclusions, it is important to consider a few crucial aspects that might impact this interpretation. First, while the unit price ratio provides insights into the relative pricing of foreign to domestic products, it does not capture the price changes over time. Notably, even if the unit price ratio has decreased over time, this does not necessarily imply that the prices of foreign products have remained static or deflationary. It is possible that foreign products experience price increases and still maintain a decreasing price ratio if domestic product prices have increased at an even higher rate. Thus, it is vital to distinguish between relative prices and their actual movement. Second, the dynamic nature of products in the market may impact relative prices and relative price changes differently. For example, if a high-end domestic product was introduced and frequently transacted upon introduction, but it replaced another equally high-end domestic product which was transacted less frequently in the past, the unit price ratio might decrease without a unit price change attached to the replacement. Third, the unit price ratio method gives weight to individual PRP within a category, but it does not factor in the importance of different categories in the entire distribution. This means that categories that are less significant might disproportionately influence the average ratio, potentially affecting the results. Given these considerations, a more targeted analysis is required to truly discern the pricing dynamics of foreign versus domestic products around the time of the Brexit referendum.

To delve deeper into the separate price evolution of foreign and domestic products, I employ the unit price relatives as discussed in the preceding section. Specifically, these encompass the direct unit price relatives of PRP observed in two adjacent periods, and the computed unit price relatives of newly introduced or re-appearing PRP in relation to near-perfect substitutes or highly analogous products from the previous period.[17]

[17]Note that in the identification of near-perfect substitutes or highly analogous PRP in the previous section, I did not

The initial step is to aggregate these unit price relatives into elementary aggregates $E_{gt}^{L,O}$. These aggregates are constructed for each category $g$ at each period $t$, and are further distinguished by their origin $O$ – either foreign or domestic. This aggregation can mathematically be expressed as:

$$E_{gt}^{L,O} = \prod_{i \in \Omega_{gt}^{O}} R_{it}^{w_{it-1}} \tag{18}$$

where $\Omega_{gt}^{O}$ denotes the set of PRP, either domestic or imported, within category $g$ transacted during periods $t$ and $t-1$. This set also covers PRP transacted in period $t$ for which at least one near-perfect substitute or highly analogous PRP exists in period $t-1$. Further, $w_{it-1}$ equals the total expenditure on PRP $i$ in period $t-1$ divided by the total expenditure on the corresponding category in period $t-1$. Given the differentiation by origin for a set of PRP, these weights sum up to one for a category grouped by origin. The superscript $L$ denotes that this formula employs the Laspeyres methodology. This suggests that the weights for aggregation are derived from the base period, which, in the context of a matched model approach, aligns with the preceding period.

Upon establishing the origin-specific elementary aggregates, I derive the origin-specific FMCG unit price index values $I_t^{L,O}$ for each period $t$. This is achieved by taking a weighted geometric mean of the elementary aggregates:

$$I_t^{L,O} = \prod_{g^O} E_{gt}^{L,O\, w_{gt-1}} \tag{19}$$

where $w_{gt-1}$ stands for the ratio of total expenditure on category $g^O$ during period $t-1$ to the total expenditure across all categories during the same period within the same origin. Finally, I generate a chained series of index values, which is accomplished by the cumulative multiplication of the individual index values.

As I aim to compute the origin-specific Fisher unit price indices, which is the geometric mean of the Laspeyres and Paasche price indices, I repeat the steps outlined in equations (18) and (19). However, a pivotal distinction is that I now employ current period weights, diverging from the previous period weights used for the Laspeyres methodology. This yields the chained origin-specific Paasche-type unit price indices, represented as $I_t^{P,O}$. Subsequently, I derive the origin-specific Fisher unit price indices via the following formula:

$$I_t^{F,O} = \sqrt{I_t^{L,O} \cdot I_t^{P,O}} \tag{20}$$

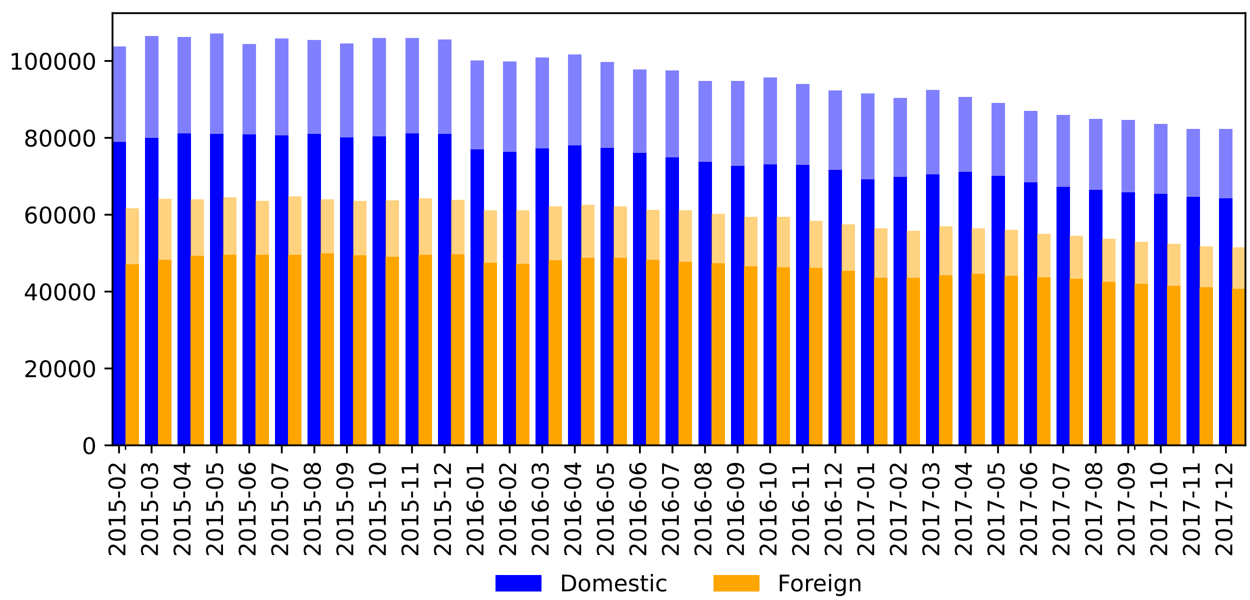
It is important to note that the resulting domestic and foreign Fisher unit price indices account for the extensive margin, as I integrate price relatives for newly introduced and re-appearing PRP throughout the computation. That is, the resulting indices are not prone to the extensive margin bias discussed in the preceding section. The number of domestic and foreign PRP transacted in two adjacent periods with newly introduced successor and re-appearing PRP is shown in Figure 18, and the corresponding change in expen-

differentiate based on the origin of the products. Consequently, I consider both domestic and foreign PRP within the same granular category as being highly substitutable for each other. This approach acknowledges that the functional and qualitative similarities of products are prioritized above their geographical origins when determining substitutability.

diture due to newly introduced successor and re-appearing PRP in Figure 19. The origin-specific Fisher unit price indices are shown in Figure 20.

Upon examining the figures, several salient patterns emerge, underlining the largely parallel dynamics of both domestic and foreign products. While there is a noticeable frequency of domestic PRP being transacted as compared to foreign PRP, the temporal trend in the number of these PRP is consistent across both origins. This indicates that the rate at which new domestic and foreign PRP appear (or re-appear) in the market is somewhat synchronized. Moreover, the influence of newly introduced and re-appearing PRP on expenditure evolves similarly for both origins. This mirrors the consistent trend in the (re-)appearance of these PRP. Finally, both foreign and domestic PRP exhibit an analogous price movement over time. Notably, there is a minor price dip preceding the Brexit referendum, succeeded by a pronounced price surge. While this trend aligns with the pattern presented in the extensive margin-adjusted Fisher unit price index (see Figure 15), Figure 20 highlights that this evolution persists when slicing up the price dynamics by origin. Interestingly, foreign PRP are slightly more inflationary than domestic PRP post-referendum, which confirms that the analysis of unit price ratios alone is not sufficient to draw conclusions on price movements.

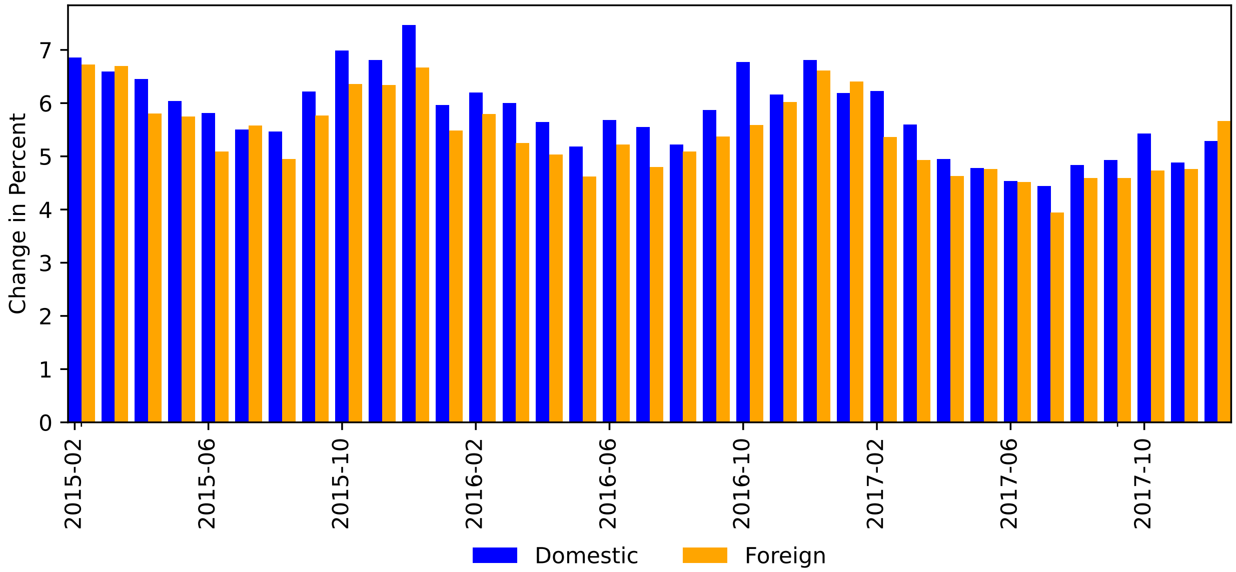
Figure 18: Temporal evolution of foreign vs. domestic products: Count of PRP in two adjacent periods (+ newly introduced PRP and re-appearing PRP)




**Note:** This figure illustrates the number of domestic and foreign PRP observed in two adjacent periods. The shaded region represents both newly introduced PRP and those that re-appeared, i.e. for those PRP I do not directly observe prices in the preceding period, but I computed them.

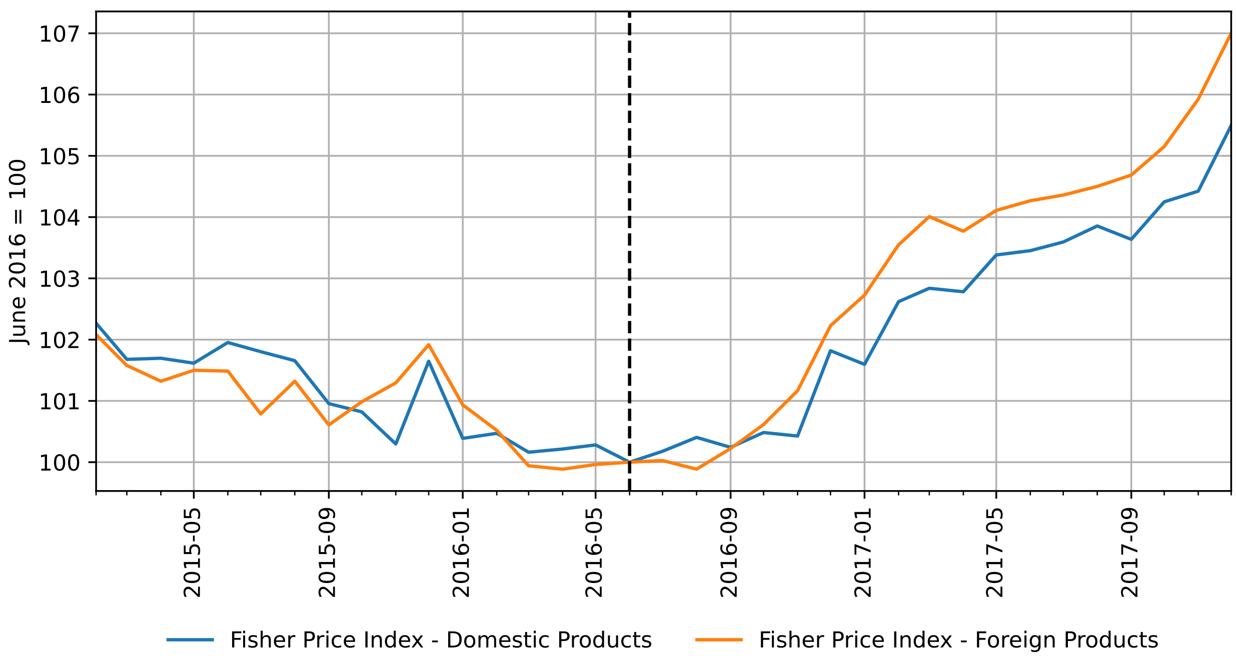
In the final part of this section, I assess relative price movements at a granular level. The question I seek to answer can be stated as follows: Are foreign products becoming relatively pricier than their domestic counterparts when I factor in a high level of comparability between the products? To investigate this, I

Figure 19: Temporal evolution of expenditure change: Impact of newly introduced and re-appearing PRP by origin




**Note:** This figure shows the change in expenditure resulting from the introduction or re-appearance of PRP. It differentiates between domestic and foreign PRP, offering insight into how these new market entries impact overall spending by origin.

Figure 20: Evolution of the FMCG Fisher unit price index (dynamic basket) distinguished by product origin




**Note:** This figure depicts the evolution of domestic and foreign Fisher unit price indices over time. The Fisher unit price indices account for the extensive margin. The figure demonstrates the price dynamics of PRP when differentiated by their origin, providing insights into relative inflation dynamics.

compute a Fisher-type elementary aggregate for each category $g$ at month $t$:

$$E_{gt}^{F,O} = \sqrt{E_{gt}^{L,O} \cdot E_{gt}^{P,O}} \tag{21}$$

The Laspeyres-type elementary aggregate, $E_{gt}^{L,O}$, represents the average price change using weights from the previous period. The details of its computation were presented in equation (18). The Paasche-type elementary aggregate, $E_{gt}^{P,O}$, represents the average price change using weights from the current period.

Having constructed the Fisher aggregates, I then create a ratio of these aggregates for foreign PRP to those of domestic PRP for each category $g$ at month $t$:

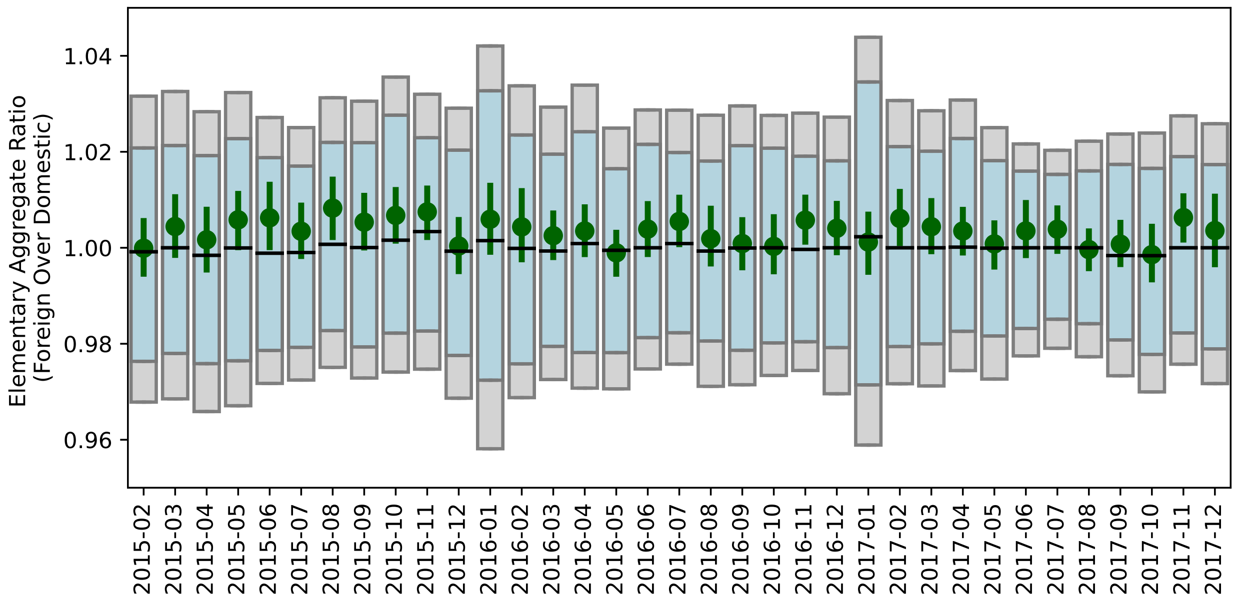
$$\hat{E}_{gt} = \frac{E_{gt}^{F,F}}{E_{gt}^{F,D}} \tag{22}$$

where the second superscript $F$ in the numerator stands for foreign, and the second superscript $D$ in the denominator for domestic.

This ratio enables me to evaluate the relative price movements of foreign products compared to close domestic substitutes. More specifically, it shows how unit prices of foreign products, say foreign low fat yoghurts, Gouda cheese, sugar fruit candies, or washing machine capsules, evolve relative to the same domestic products within the same retailer. I utilize box plots to visualize the distribution of the computed ratios across all months, focusing particularly on the median, mean, and various percentiles to assess the central tendencies and dispersions in the data. The box plot is shown in Figure 21. The median and the mean – together with the 95 percent confidence interval – as well as the percentiles reveal that the pricing dynamics for foreign PRP do not differ strongly from those of domestically produced substitutes. More specifically, the median's consistent proximity to the value of 1 suggests a balanced price dynamic between foreign and domestic PRP. In line with that, the mean stays above but very close to 1 with the confidence interval usually including 1. This underlines the results from the analysis before, which showed that the aggregated price dynamics of foreign PRP are marginally more inflationary than those of domestic PRP.

The result that foreign products have not become significantly pricier than their domestic counterparts despite the Brexit-vote depreciation might seem counter-intuitive at first glance. However, this phenomenon is not isolated to the UK. The forthcoming research by Beck et al. (2024) delineates a similar trend in countries such as Brazil, Chile, Colombia, Mexico, and Peru. In these countries, despite a substantial appreciation of the US dollar against their respective currencies, the relative prices of foreign products vis-à-vis domestic substitutes remained remarkably stable. This stability is even more surprising given the predominance of the US dollar as the invoicing currency for imports in these countries, as noted by Gopinath et al. (2020). Moreover, there are plausible, yet speculative, economic explanations that could justify such an outcome. First, domestic products rely on imported raw materials or components as shown by Breinlich et al. (2021). A weaker Pound sterling could increase the cost of these imports, leading domestic firms to raise their prices. This phenomenon may even cause domestic products to become relatively more expensive than their imported

Figure 21: Relative price dynamics of foreign vs. domestic PRP: Box plot of $\hat{E}_{gt}$




**Note:** This figure visualizes the distribution of the ratio $\hat{E}_{gt}$ from equation (22). The grey region represents the 10th to 25th and 75th to 90th percentiles, respectively. The blue region spans the interquartile range, covering the 25th to 75th percentiles. The median is indicated by the black solid line, while the mean is represented by the green dot, which is further complemented by its 95 percent confidence interval.

counterparts, especially if the latter has long-term pricing agreements or hedges against currency fluctuations. In line with that, the period around the Brexit referendum might have led to uncertainties and disruptions in supply chains. This could have temporarily increased the cost of domestic production, especially if there was stockpiling or if firms faced challenges in getting necessary inputs, whether domestically or from abroad. Second, distributors or retailers may react to cost shocks by adjusting the entire price structure. This is underlying the contribution by Cole & Eckel (2018) who explore the impact of tariff increases on retail prices. As an example, if higher markups are charged for domestic products, their prices may be increased over-proportionally. Third, local production costs, or local costs involved in bringing the products to the shelves, might create a disparity between prices and imported costs, which remains unaffected by fluctuations in the exchange rate. This could explain why prices exhibit a delayed and partial response to exchange rate variations. This is a key finding of Nakamura & Zerom (2010), who empirically analyse the determinants of incomplete pass-through in the coffee industry, utilizing microdata on sales and prices. Moreover, they find that delayed pass-through occurs almost entirely at the wholesale rather than the retail level. Fourth, if firms expect the Pound sterling to continue depreciating, they might preemptively raise prices. This can be especially true for domestic firms that anticipate further increases in their import costs. Fifth, it is possible that there were changes in consumer behavior during this period. For example, a rise in economic nationalism could lead consumers to prefer domestic products even at a slightly higher price, allowing distributors or retailers to charge a higher markup.

## 3.5. Distributional effects

In this concluding section, the objective is to investigate both the variance in inflation rates and distributional consequences across households from different social classes. The analysis targets the welfare implications stemming from fluctuations in the exchange rate, specifically examining the diverse impacts of the Brexit-vote depreciation across distinct social classes in the UK. As the subsequent inflation was one of the most immediate effects of the Brexit vote – even before the actual Brexit occurred – it is important to analyze i) if the impact was likely felt by every individual in the UK, and ii) the variations in this impact amongst different social classes.

This analysis resembles the work of Breinlich et al. (2021), who investigate in their final chapter how the Brexit vote has affected the cost of living and real wages in the UK, segmented by household (type). They claim that households that spend a larger portion of their budgets on product groups with higher import shares faced larger cost of living increases, as the increase in inflation was more pronounced in product groups with higher import shares. They first compute the expenditure share of each COICOP class for 4,912 households and then calculate the effect of the Brexit-vote depreciation on the price of each household's consumption basket. Their findings indicate a notable variation across households in terms of how the depreciation influenced living costs. Specifically, they find that the majority of households experienced an inflation rate within the 2 percent to 4 percent range by June 2018, with a household situated at the 75th percentile of the distribution facing a price surge that was 1 percentage point higher than that encountered by a household at the 25th percentile. When linked to disposable household income, however, they demonstrate that there is minimal variation in inflation across different income deciles. This suggests that the surge in living costs triggered by the Brexit-vote depreciation is distributed fairly evenly across various income groups. This phenomenon occurs because they did not identify any systematic correlation between household income levels and the proportion of expenditures allocated to imports.

By contrast, my analysis takes a more direct route to evaluate the influence of the Brexit vote on different household types' cost of living. Rather than leveraging the variations in expenditure shares across product groups and associating them with respective price increases, I exploit the richness of the scanner dataset and compute social class-specific price indices, incorporating real-time spending patterns and adjustments on the extensive margin.

To facilitate this analysis, I incorporate the household identifier associated with each transaction. Specifically, I cross-reference transactions with a supplementary household dataset, which offers household information attained through survey questionnaires. This dataset provides detailed attributes for each household, such as social class and annual income of the head of the household, household size, and other demographics.

The classification of social classes I employ is the socio-economic grade system in the UK, which divides the population into social classes based on occupation. The following classes are defined: *AB - Upper Middle Class:* This group typically includes those with higher managerial, administrative, or professional occupations. They generally have higher levels of income and education. *C1 - Lower Middle Class:* This group often encompasses supervisory, junior managerial, administrative, or professional roles. They usually have a level of post-school qualifications. *C2 - Skilled Working Class:* This group captures people with skilled manual occupations that typically have vocational training but not necessarily a university degree. *D - Working Class:* This group includes semi-skilled and unskilled manual workers. They may have finished schooling but usually without advanced qualifications. *E - Lowest Level Of Subsistence:* This group represents those at the lowest levels of subsistence including casual or lowest-grade workers, pensioners, and others with a minimal income. The system essentially categorizes individuals based on their job roles, with the implication that these roles correlate with education levels, income, and, to some degree, lifestyle and consumption habits.[18]

In the analysis, I start with the aggregation of transactions at the PRP-household level on a monthly basis. This granular approach retains the richness of the dataset, contrasting with, for instance, an aggregation at the PRP-household group level (e.g., social classes).[19] As a result, rather than observing aggregate monthly expenses and prices of a PRP spanning all households within a social class, I am equipped with detailed insights into the monthly expenses and prices linked to individual households, each assigned to a social class. This granular perspective allows to capture variations in spending behaviors even within a social class.

Table 11 provides both demographic and transaction details segmented by social class.[20] There is a clear trend evident in the relationship between mean income and social class designation. Specifically, as one progresses from the 'Lowest Level of Subsistence' to the 'Upper Middle Class', there is a consistent increase in mean income. This consistent relationship between mean income and social class designation justifies to use the terms social class and income class interchangeably throughout this section. Moreover, the 'Lower Middle Class' stands out as the group with the largest sample size. It registers the highest number of households, monthly observations and expenses. This suggests that the 'Lower Middle Class' is particularly significant, both in terms of its representation in the dataset and its purchasing activity.

While inflation is usually discussed as a broad economic indicator, its effects can vary widely across the population. By examining its distributional impact, especially in the aftermath of pivotal events like the Brexit vote, I seek to provide a comprehensive view of the societal implications. For instance, if inflation affects working-class households more strongly than middle class households, it could exacerbate income inequality. Moreover, the way households across different social classes respond to price changes can offer insights into consumer behavior and can have broader economic implications. For example, lower-income households might switch to cheaper substitutes or reduce consumption of non-essential items, which could lead to a slowdown in economic activity. In addition, a granular understanding of how inflation impacts different social classes can guide fiscal policies. If certain social classes are disproportionately affected, fiscal

[18] This grading system has been a tool for market research in the UK for many years, helping to target specific demographics in, e.g., advertising campaigns. For further information on this classification, see National Readership Survey (NRS) - Social Grade Definitions.

[19] In prior sections, I aggregated transactions monthly at the PRP level, omitting the household dimension.

[20] Given the consideration of the extensive margin and the use of unit prices, I utilize the reduced scanner data sample shown in the second column of Table 2. Notably, products measured in 'Pieces', those lacking a brand name, and those with either missing volume descriptions or ambiguous ones like 'Loose', 'Random Weight', 'All Other Sizes', or 'Standard' are excluded.

Table 11: Demographic and transaction information by social class

| | Social Class | | | | |
|---|---|---|---|---|---|
| | **AB: Upper Middle Class** | **C1: Lower Middle Class** | **C2: Skilled Working Class** | **D: Working Class** | **E: Lowest Level Of Subsistence** |
| **Number of HH** | 8,149 | 15,153 | 6,826 | 5,362 | 3,694 |
| **Mean Income in GBP** | 49,300 | 34,500 | 31,450 | 22,600 | 12,100 |
| **Mean HH Size** | 2.82 | 2.63 | 3.01 | 2.85 | 2.15 |
| **Total Monthly Observations** | 15,176,606 | 27,903,778 | 13,568,029 | 9,504,813 | 5,414,987 |
| **Number of Products** | 114,311 | 119,065 | 111,389 | 106,942 | 101,563 |
| **Number of Retailers** | 81 | 80 | 81 | 81 | 80 |
| **Number of PRP** | 406,164 | 497,089 | 388,874 | 356,229 | 326,059 |
| **Number of Categories** | 1,608 | 1,607 | 1,596 | 1,583 | 1,569 |
| **Sum of Expense (in GBP)** | 35,427,768 | 62,366,076 | 29,761,364 | 20,501,898 | 12,084,058 |

**Note:** This table presents demographic and transaction information by social class in the reduced scanner dataset sample covering the years 2015 to 2017. A household's social class is determined by the socio-economic status of the head of the household. A household's income is determined by the annual pre-tax earnings of the head of the household. In the dataset, incomes are categorized into distinct brackets, each spanning £9,999. Specifically, these brackets are delineated as follows: Income bracket 1: £0 - £9,999, income bracket 2: £10,000 - £19,999, and so forth, up to income bracket 7: £60,000 - £69,999. Beyond this, there is an open-ended income bracket 8 starting at £70,000, for which I have assumed an upper limit of £99,999 for linear interpolation purposes.
A challenge arises when I seek to interpret the mean values derived from these brackets. Since the brackets represent a range rather than a precise figure, linear interpolation offers a technique to estimate more specific income values from these mean bracket figures. To begin, I calculated the midpoint of each bracket. For instance, the midpoint of bracket 1 (spanning £0 - £9,999) is £4,999.5. Given a mean value from the dataset, such as the 3.95 for the 'Lower Middle Class', the task is to identify its exact position between two bracket midpoints. Using the 3.95 example, this value falls between the midpoints of bracket 3 (£24,999.5) and bracket 4 (£34,999.5). To interpret this, consider that 3.95 is 0.95 units above 3. This suggests it is 95 percent of the way from the third to the fourth bracket. Given a consistent £10,000 interval between bracket midpoints, the interpolated income value for 3.95 is £34,499.5. This approach is repeated for all mean values, which makes it possible to map categorical average incomes to more exact estimated values.

policies can be designed to support these households. Finally, pivotal events like the Brexit referendum often come with public discourse. If certain parts of the population are bearing most of the economic distress, it can lead to social discontent and political upheavals.

The preceding section illustrated similar relative price dynamics between domestic and foreign products. While this provides an understanding of market trends, it does not reveal how different social classes are affected. Low-income households might prioritize basic necessities, while high-income households might purchase a larger share of luxury items. If inflation differs among these lines, there can be distributional effects. The elasticity of demand may also differ across social classes. High-income households might be less sensitive to price changes, while low-income households might be more price elastic and adjust their consumption patterns more significantly in response to price fluctuations. Provided that alternatives exist, this can have a dampening effect on income inequality. On the contrary, low-income households usually have tighter budget constraints. This implies that even small price changes can have significant implications, i.e. the actual impact on household budgets can differ across social classes, even if the inflationary effect is similar.

In analyzing consumer behavior, a common presumption is that households with lower incomes tend to purchase more affordable products compared to those with higher incomes. This finding was established, e.g., by Cravino & Levchenko (2017) who study the price and distributional effects of the 1994 Mexican peso devaluation. They show that poorer Mexican households consume lower-priced products, while richer Mexican households consume higher-priced products within the same product category. Additionally, it was observed that the more affordable products were subject to a more pronounced surge in prices, thereby escalating the living expenses disproportionately for poorer households as compared to richer ones. Utilizing scanner data on FMCG in the United States from 2004 to 2013, Kaplan & Schulhofer-Wohl (2017) identified significant disparities in the prices paid by different households within the same product category. Moreover, they observed variations in the prices paid for identical products. This suggests that lower-priced purchases are not solely attributable to selecting different, possibly lower-quality, products, but might also be influenced by opting for sales promotions.

With access to detailed data on household expenditure and pricing, I can explore the hypothesis that households with lower incomes opt for more affordable products – whether as a result of inherently lower priced products or through sales promotions – compared to those with higher incomes. To do so, I calculate the average unit price of PRP within each category that households from a specific income class purchased from 2015 to 2017:

$$\bar{P}^U_{gs} = \frac{\sum_{i \in g} \sum_{i \in s} P^U_i}{N} \tag{23}$$

where $P^U_i$ represents the unit price of PRP $i$. The numerator sums up all unit prices of PRP that fall under category $g$ and were acquired by households of social class $s$. This sum is then divided by $N$, the total number of such PRP, to derive the average unit price $\bar{P}^U_{gs}$.

Next, I assess the variation in the average unit price by determining its relative difference for each category $g$ and social class $s$ compared to the lowest income class, specifically the 'Lowest Level Of Subsistence'. As an illustration, the relative difference in average unit prices for a category $g$ in the 'Working Class' is defined as:

$$\Delta \bar{P}^U_{g\omega} = \frac{\bar{P}^U_{g\omega} - \bar{P}^U_{g\iota}}{\bar{P}^U_{g\iota}} \tag{24}$$

where $\iota$ denotes 'Lowest Level Of Subsistence' and $\omega$ represents the 'Working Class'.[21]

The distribution of these relative differences in unit price is presented in Table 12. The observed statistics, including the mean, median, and quantiles, reveal a consistent pattern: Moving to higher-income classes, households tend to opt for relatively pricier product varieties. This indicates distinct purchasing behaviors across social/income classes in line with the findings of Cravino & Levchenko (2017) following the 1994 Mexican peso devaluation. If inflation is correlated to unit prices within categories, this could lead to distributional effects.[22]

Having highlighted one specific purchasing trend across social classes, I now move to construct social class-specific price indices. Any variation in inflation across social classes hinges on two factors. First, the

[21] I selected the symbols omega ($\omega$) and iota ($\iota$) to prevent any confusion with $w$, which is already designated to represent weights.

[22] While the choice between lower-priced and higher-priced products within categories is one distinction, there are other possibilities, like package sizes, branded versus non-branded products, etc. Additionally, cross-category variations might play a role, such as richer households preferring luxury items that are rarely purchased by those in lower-income classes. A dynamic basket index, segmented by social class, captures all of these effects, even if they are not made explicit.

Table 12: Distribution of relative mean unit price differences across categories and social classes, relative to the class 'Lowest Level Of Subsistence'

| | Social Class | | | |
|---|---|---|---|---|
| | **AB: Upper Middle Class** | **C1: Lower Middle Class** | **C2: Skilled Working Class** | **D: Working Class** |
| **Count** | 1,529 | 1,530 | 1,524 | 1,515 |
| **Mean** | 0.12 | 0.07 | 0.05 | 0.03 |
| **Mode** | 0 | 0 | 0 | 0 |
| **Std** | 0.38 | 0.25 | 0.23 | 0.21 |
| **Min** | -0.54 | -0.51 | -0.51 | -0.52 |
| **Max** | 3.36 | 2.32 | 2.02 | 1.68 |
| **10%** | -0.09 | -0.09 | -0.09 | -0.11 |
| **25%** | -0.01 | -0.01 | -0.03 | -0.04 |
| **50%** | 0.04 | 0.02 | 0.01 | 0 |
| **75%** | 0.13 | 0.09 | 0.06 | 0.04 |
| **90%** | 0.36 | 0.26 | 0.21 | 0.16 |

**Note:** This table presents the distribution of $\Delta\bar{P}^U_{gs}$, i.e. of the relative mean unit price differences, segmented by social classes and compared to the lowest income class, on a category-level, spanning the period 2015-2017. The 'count' denotes the number of categories. A household's social class is determined by the socio-economic status of the head of the household.

price changes of products commonly bought by households in different social classes (e.g., more affordable versus pricier items, small package sizes versus large package sizes, etc.) and the shifts in expenditure as a response to price fluctuations.

In constructing a dynamic basket index, such as the Fisher index used in earlier sections, segmented by social class, I capture potential variations in purchasing and substitution patterns. Furthermore, by computing price relatives for newly introduced or re-appearing products, I address the price effects stemming from the extensive margin.

To derive the Fisher unit price indices specific to each social class, I first consolidate the data by households within each social class. This results in monthly unit prices and total expenditures on a PRP basis for each social class. Thereafter, I identify the PRP for which I cannot determine a price relative due to their absence in transactions from the previous period. Given that I computed unit price relatives for new and re-appearing PRP in Section 3.3., I integrate these values into the current datasets for each social class.[23] Equipped with unit price relatives and PRP expenditures, I can now create the extensive margin-adjusted Fisher unit price index by social class. Specifically, I aggregate the unit price relatives into elementary aggregates, denoted as $E^L_{gst}$. These aggregates are constructed for each category $g$ and social class $s$ at each period $t$. This aggregation can formally be expressed as:

$$E^L_{gst} = \prod_{i \in \Omega_{gst}} R_{it}^{w_{it-1}} \tag{25}$$

where $\Omega_{gst}$ represents the set of PRP within category $g$ bought by households from social class $s$ during periods $t$ and $t-1$. Importantly, this set also includes PRP transacted in period $t$ with a corresponding near-perfect or highly analogous substitute in period $t-1$. Further, $w_{it-1}$ signifies the proportion of expenditure on PRP $i$ in period $t-1$ relative to the total expenditure on its respective category and social class in that same period. Due to the class-specific nature of the aggregation, these weights, when summed within a category by social class, total to one. The superscript $L$ indicates the use of the Laspeyres approach, implying that

[23]Recall that, if unit price relatives are not directly observable in the dataset, I first compute PRP in relation to near-perfect substitutes from the previous period. For those PRP that do not have a near-perfect substitute, I compute PRP in relation to highly analogous products from the previous period.

the aggregation weights are sourced from the base (=preceding) period.

Having defined the social class-specific elementary aggregates, I can then determine the FMCG unit price index values $I_{st}^{L}$ for each period $t$ specific to each social class $s$. These index values are calculated using a weighted geometric mean of the elementary aggregates:

$$I_{st}^{L} = \prod_{g} {E_{gst}^{L}}^{w_{gst-1}} \tag{26}$$

where $w_{gst}$ represents the proportion of total expenditure by social class $s$ households on category $g$ in period $t-1$ to their overall expenditure across all categories in the same period. Following the calculation of these individual index values, I produce a chained series by successively multiplying the values together.

To compute the social class-specific Fisher unit price indices - essentially the geometric mean of Laspeyres and Paasche price indices - I revisit the procedures described by equations (25) and (26). The key modification involves using current period weights instead of the preceding period weights, which were applied in the Laspeyres methodology. This adaptation gives rise to the social class-specific Paasche unit price indices, denoted as $I_{st}^{P}$. With both the Laspeyres and Paasche indices in hand, I can then compute the social class-specific Fisher unit price indices using the equation:

$$I_{st}^{F} = \sqrt{I_{st}^{L} \cdot I_{st}^{P}} \tag{27}$$

In Figure 22, the social class-specific Fisher unit price indices are depicted. Post-referendum, every social class undergoes a comparable inflation dynamic, with either stable or marginally declining prices preceding the referendum. In terms of inflation figures, all social classes experienced an inflation rate within the 4.7 percent to 8.7 percent range by December 2017. Notably, the 'Upper Middle Class' witnesses the highest inflation rates as its curve remains relatively flat before the referendum and ascends sharply afterwards. Conversely, the 'Working Class' witnesses the lowest inflation. This distinction suggests that 'Working Class' households might adjust their expenditures more significantly in response to price shifts, possibly including more pronounced sales-driven purchases. The magnitude of this inflation disparity is significant. Approximately 18 months post-referendum, the inflation rate for the 'Working Class' is roughly 4 percentage points lower than that of the 'Upper Middle Class'.

In contrast to the findings by Breinlich et al. (2021), my results imply that there is considerable variation in inflation across different income classes following the referendum. Related to the findings by Kaplan & Schulhofer-Wohl (2017), I can confirm that, on average, household-level inflation mirrors the trend observed in aggregate inflation. However, the analysis diverges when examining the correlation between inflation and household income. Contrary to the findings of Kaplan & Schulhofer-Wohl (2017), who identified a cumulative average inflation of 33 percent for households with incomes below $20,000 and 25 percent for those with incomes above $100,000 between 2004 and 2013, the observations show a different pattern. In this study, the 'Upper Middle Class' with a high income level experiences a more pronounced inflation compared to all other classes with a lower income level. Furthermore, the 4 percentage points difference in inflation rates between the 'Upper Middle Class' and the 'Working Class' over a span of 1.5 years deviates substantially from the 8 percentage points difference identified by Kaplan & Schulhofer-Wohl (2017) over a 9 year period. This deviation could potentially be attributed to the unique event of this study, characterized by a significant currency depreciation, that could potentially cause stronger and specialized reactions in price movements in line with, e.g., Colavecchio & Rubene (2020), who show that relatively large exchange rate changes entail higher exchange rate pass-through. Another significant distinction in this study is the methodology employed to calculate price indices. Kaplan & Schulhofer-Wohl (2017) do not adjust the Laspeyres, Paasche and Fisher price indices to accommodate the dynamic nature of FMCG or to incorporate extensive margin adjustments. In particular, they state that "*we use only those specific goods - defined by barcodes - that each household purchases at both dates. Thus, in all of our indexes, we measure inflation for the subset of goods that households buy repeatedly. This inflation rate may differ from an inflation rate that includes goods bought less frequently, but we have no way to compute the latter rate at the household level*" (p.25). It is likely that the non-inclusion of this dynamic aspect of FMCG is a significant contributor to the disparities observed in the relation of household-specific inflation rates and income levels.

In order to gauge the real impact on household budgets, it is essential to relate the different price evolution to the mean income level of the respective social class. As detailed in Table 11, the average income of a 'Working Class' household's main earner is less than half that of an 'Upper Middle Class' household's counterpart, standing at 22,600 GBP in comparison to 49,300 GBP. Given these disparities, the inflation rate of 4.7 percent over the 18 months following the referendum for the 'Working Class' is likely to have a more profound economic impact than the 8.7 percent inflation experienced by the 'Upper Middle Class' during the same period. For example, the 'Working Class' can be expected to operate under more stringent budgetary constraints. The combination of a higher proportion of income spent on essential products and a lower disposable income means that any increase in prices can substantially distort their carefully balanced budgets. Unlike the 'Upper Middle Class' who might cut back on a few luxuries or delay a discretionary purchase when faced with inflation, the 'Working Class' may find themselves making harder choices, such as resorting to cheaper but possibly lower-quality alternatives. Thus, although 'Working Class' households might have partially offset the post-referendum inflation through expenditure adjustments, they could not entirely evade its effects. With their constrained budgets, the net inflation experienced - after accounting for any shifts in spending patterns - poses a significant economic burden on them. Reflecting on the polling results, it is worth noting that working-class voters, who predominantly favoured the 'Leave' option, are among the groups most significantly affected by one of the most immediate economic effects of the Brexit decision.

The households most severely impacted, however, are those at the lowest level of subsistence. This group includes individuals who are often grappling with significant economic and social challenges. It is a diverse group of people, including those engaged in casual labor, lowest-grade occupations, as well as pensioners who are primarily dependent on state pensions or benefits. Their income levels are typically characterized as being at or below the country-specific poverty line, and they might frequently encounter difficulties in meeting basic living standards. It is also worth noting that the individuals in this group may experience higher levels of financial volatility, with incomes that might vary significantly from month to month, particularly for those engaged in casual labor. Their consumption habits can be markedly different from those in higher income classes. Due to constrained financial resources, this group is more likely to prioritize essential products, often opting for cheaper, budget-friendly alternatives. They might also display a higher propensity to engage in price-sensitive behaviors, such as making use of discounts, sales, and offers to manage their limited budgets. It is striking that inflation experienced by households at the lowest level of subsistence (6.6 percent over the 18 months following the referendum) is comparable to inflation experienced by the middle class, and thus remarkably higher than that experienced by the working class. Combined with their tight budgets, the households at the lowest level of subsistence disproportionately bear the brunt of the Brexit-vote depreciation. It seems like their coping strategies are not as resilient as those observed in the 'Working Class'. Put differently, why did this group not manage to evade the inflationary effects to a larger extent? Several plausible, yet speculative, economic explanations could justify this observation. First, their consumption may predominantly be targeted at the most affordable variants of essential products (i.e. for which the demand is inelastic), which implies that they have limited opportunities to switch to alternative products, even if the most affordable variants undergo price hikes. Thus, price increases for these products consumed directly translates to inflation experienced by this group. Second, in times of macroeconomic distress like post-referendum, retailers might have reduced the frequency and extent of discounts and sales, a strategy that disproportionately affects households at the lowest level of subsistence. Third, their restricted mobility implies difficulties to access retailers that could potentially shield them from inflation. Fourth, they might not have easy access to credit facilities to smooth consumption during times of high inflation.

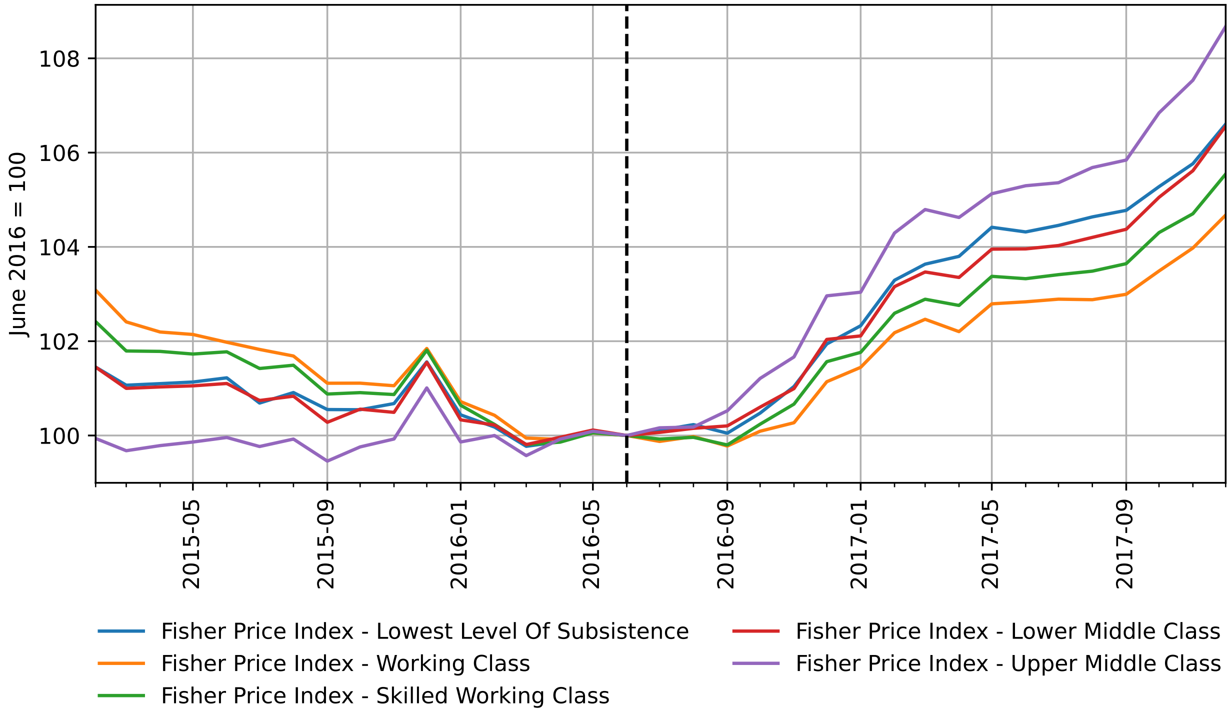
The results of this section reveal the profound welfare and distributional implications of the Brexit-vote depreciation. More specifically, the inflationary impact was felt throughout all social classes in the UK. Most alarmingly, however, is the finding that lowest-income households suffered the most.

## 3.6. Summary and conclusions

The Brexit vote on June 23, 2016 initiated the UK's departure from the European Union. Numerous studies have used the subsequent depreciation of the Pound sterling as an event study to analyze the impact of exchange rate fluctuations on prices. These studies consistently indicate a significant pass-through from this depreciation to both UK border and consumer prices. Consequently, the post-referendum price surge represents one of its most immediate nationwide economic effects.

This paper examines retail price dynamics around the time of the referendum from a microscopic perspective, using an exceptionally detailed scanner dataset of 'fast-moving consumer goods' (FMCG). FMCG

Figure 22: Evolution of the FMCG Fisher unit price index (dynamic basket) distinguished by social class




**Note:** This figure depicts the evolution Fisher unit price indices over time. The Fisher unit price indices are social class-specific and account for the extensive margin.

prices exhibited a downward movement prior to the referendum, but started to move upward following the referendum. This evolution is first obtained by utilizing a static basket and static weights price index. As this price index ignores changes in both the set of products and expenditure weights over time, I also compute a dynamic basket with dynamic weights Fisher price index. Surprisingly, under this specification, prices exhibited a sideways movement following the referendum. This may point to a change in the basket of products and/or a corresponding adjustment of spending patterns. I argue, however, that a standard matched model approach bears a crucial limitation: It overlooks extensive margin adjustments. These are price changes of newly introduced and re-appearing products, which command a considerable expenditure share and have inflationary effects. By calculating price relatives of these products in relation to near-perfect substitutes or highly analogous products from the previous period, I gain clarity on the price dynamics. Specifically, I find that prices exhibited a *slight* downward evolution prior to the referendum, but started to move *sharply* upward following the referendum, which implies that inflation was more pronounced than predicted by the fixed basket and weight price index. Furthermore, my research indicates that the Brexit vote serves as a significant turning point. Specifically, I find an acceleration in inflation driven by adjustments at the extensive margin in the period following the referendum. These findings underscore the significance of adjusting price indices for the extensive margin. Neglecting to do so can introduce substantial distortions, particularly as these adjustments tend to inflate prices, leading to potential overestimations of price reductions and underestimations of price hikes.

Recognizing the significance of extensive margin adjustments, I integrate them into subsequent analyses. First, I show that imported products – which are on average cheaper than their domestically produced substitutes – did not become significantly pricier in relative terms in the aftermath of the Brexit referendum, a result which may initially seem paradoxical. I argue that this can be attributed to factors like the foreign share in domestically produced products or distributor and retailer pricing strategies that adjust entire price structures in response to cost shocks. Second, I show that the Brexit vote-induced depreciation shock on the Pound sterling had profound welfare and distributional implications. Although the inflationary impact was felt throughout all social classes, the magnitude of the impact notably varied between them. Specifically, the 'Upper Middle Class' experienced the steepest price increase, and the 'Working Class' the least. This suggests the 'Working Class' either selected products with minimal price increases or adjusted their spending habits to circumvent some of the inflation. However, even with strategic spending shifts, they could not entirely escape the inflationary impact. Given their tighter budgets, this implies that the 'Working Class' – notably major supporters of the 'Leave' campaign – were among the most impacted by the subsequent price hikes. Most alarmingly, however, is the finding that households at the lowest level of subsistence experienced high inflation (6.6 percent over the 18 months following the referendum, which is similar to inflation experienced by the 'Lower Middle Class') and thus suffered effectively the most from the Brexit vote-induced depreciation shock on the Pound sterling. A potential explanation for this observation is that consumption of the lowest income households may predominantly be targeted at the most affordable variants of essential products (i.e. for which the demand is inelastic), which implies that they have limited opportunities to switch to alternative products, even if the most affordable variants experience price increases.

This paper also touches upon the potential benefits of incorporating scanner data into the calculation of official inflation statistics. The analysis illustrates that utilizing the detailed and extensive information available in scanner data, as opposed to adhering to the methodology traditionally used by the UK Office for National Statistics for computing the Consumer Price Index, yields distinct inflation figures. When combined with theoretical insights into the advantages of utilizing scanner data, this discrepancy suggests that the approach could enhance the accuracy of inflation measurements.

Finally, the conclusions derived from this study lead to a series of questions, warranting further exploration. Just to name a few: To what extent do manufacturers, wholesalers, or retailers employ strategic behaviors concerning the prominent role of extensive margin adjustments? Is the observed phenomenon, where imported FMCG products have not experienced a significantly stronger price surge compared to domestically produced substitutes following a sharp exchange rate depreciation, a characteristic exclusive to the particular event and economy studied, or is it a generalizable outcome? And what are the exact mechanisms at play? Similarly, while other studies indicate a higher inflation rate for lower-income households, my findings do not align with this pattern. Is this discrepancy due to unique attributes of the event and economy I have analyzed, or might it challenge prevailing notions on the subject? Furthermore, could the observed discrepancy be attributed to working class households selecting products with minimal price increases, by adjusting spending habits, or by engaging in more sales shopping? Correspondingly, why did the lowest income households not manage to evade the inflationary effects to a larger extent? And finally, how would the results change when the analysis is broadened to encompass all product categories typically covered in a Consumer Price Index, beyond the scope of FMCG?

# 4. Anti-poor *and* anti-rich: Product-downgrading and the distributional effects of UK inflation in the wake of the Brexit vote

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**Abstract**

The Brexit vote of June 2016 resulted in a massive depreciation of the British pound and a strong increase of retail prices in the United Kingdom. In this paper, we analyze the distributional effects of this inflationary episode, focusing on households' decision to adjust their consumption behavior at the extensive margin within narrowly defined products. Using a very granular data set on household purchases of fast-moving consumer goods, we demonstrate that households at an intermediate income level engaged in *product-downgrading*, i.e. they switched from higher-priced varieties of a given product to lower-priced varieties, and thus limited the effect of the overall price increase. By contrast, poor households had no scope for product-downgrading since they already consumed the lowest-priced varieties. Rich households, finally, also did not change the mix of varieties they consumed – probably because their higher income allowed them to tolerate the price increase.

**Keywords**

Inflation, Distributional Effects, Exchange Rate Pass-through

**JEL-Codes**

E31 · D31 · F15 · F31 · F41

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## 4.1. Introduction

In this paper, we explore the distributional effects of inflation, focusing on the massive depreciation of the British pound in the wake of the June-2016 Brexit vote. The "Brexit depreciation" represents a rare example of an exogenous inflation shock since the outcome of the referendum came as a surprise, was not associated with macroeconomic turmoil, and since it raised the prices of both imported final goods and imported intermediate goods (Breinlich et al., 2021). Hence, it resulted in a price increase across a wide range of goods, and the consequences of this inflationary shock are not confounded by fluctuations of GDP or other macroeconomic variables.

Focusing on the evolution of British inflation between January 2016 and December 2017, we analyze how different income groups were affected by the overall price increase. While it is well-known that effective inflation rates may differ across different parts of the population – e.g. because of group-specific expenditure shares, combined with a heterogeneous evolution of prices, or because of different abilities to alter the composition of overall spending – we focus on one particular aspect that is likely to contribute to different inflation experiences: households' ability and willingness to cushion the overall impact of the price increase by engaging in *product-downgrading*, i.e. by replacing more expensive varieties of a given product by less expensive varieties. Using a granular data set on household purchases of fast-moving consumer goods (FMCG), we are able to explore how prices paid at the product level evolved over time. More specifically, we compute *volume-share-weighted average unit prices* for a wide range of products and analyze whether the evolution of these averages significantly differed between income groups.

The results of our analysis suggest that, when we focus on the extent of product-downgrading, the distributional consequences of the Brexit depreciation were anti-poorest and – to some extent – anti-rich: this is because the poorest households in our sample tend to purchase the most affordable varieties within narrowly defined products, limiting their ability to further switch to more affordable varieties during the inflationary period following the Brexit referendum. In contrast, middle income-households have more flexibility to adjust their purchasing habits to evade inflation, resulting in lower inflation rates compared to the poorest households. Wealthier households, despite having the capacity to substitute away from more expensive varieties, apparently choose not to, leading them to encounter inflation rates higher than those experienced by poor households, but still below the ones experienced by poorest households. While our study focuses on a particular historical episode that lends itself to an event-study research design, we believe that the constellation we identify is of general relevance and therefore contributes to a better understanding of the distributional effects of price increases.

The rest of this paper is structured as follows: in Section 4.2., we review the relevant literature on the distributional effects of inflation. Section 4.3. shortly summarizes the evolution of exchange rates, prices and macroeconomic aggregates shortly before and after the Brexit vote of June 2016. In Section 4.4., we present the data set that is underlying our analysis. Section 4.5. starts by describing our approach to compute volume-share-weighted price averages for different products. It then demonstrates that these averages significantly differ across income groups, with low-income households purchasing a bundle of lower-priced varieties than medium-income and high-income households. In a next step, we compute *price relatives* at the product level, which allow tracing the evolution of price averages over time. We show that price increases for medium-income households are significantly lower than price increases for low-income and high-income households. While these differences could be driven both by changing volume weights and a heterogenous evolution of variety-prices, we show that the difference between a Paasche index at the product level (which allows for changing volume weights) and a Laspeyres index (which keeps weights fixed) is lowest for medium-income households. Moreover, we demonstrate that the difference in Paasche indices across income groups disappears if we restrict the sample to varieties purchased in adjacent periods. We interpret this as evidence that medium-income households stop purchasing expensive varieties and replace them by other varieties, thus cushioning the overall effect of inflation. Section 4.6. summarizes our findings and offers some conclusions.

## 4.2. Relevant literature

Our work primarily draws from (and contributes to) various strands of the literature on the distributional effects of inflation.[1]

Ha et al. (2019) survey the literature on distributional effects of inflation and identify three direct channels through which inflation may vary across the income distribution: The composition of income channel (e.g., labor income vs. profits), the composition of assets channel (e.g., cash vs. financial products) and the composition of consumption baskets channel. Our study contributes to a better understanding of this third channel which states that, because households choose different product categories (e.g., meat vs. vegetables), or use differently priced versions within the same product categories (e.g., chicken vs. pork), effective inflation rates may differ.

Due to the scarcity of detailed micro data, much of the related literature has concentrated on quantifying the extent to which variations in expenditure shares across different product categories result in disparities in inflation rates (Michael, 1979, Hagemann, 1982, Cage & Garner, 2002, Garner & Ruiz-Castillo & Sastre, 2003, Crawford & Oldfield, 2002, Hobijn & Lagakos, 2005, Gürer & Weichenrieder, 2020, Möhrle & Wollmershäuser, 2021). However, the omission of the within-category dimension has faced some criticism. Jaravel (2021) emphasizes the importance of considering spending patterns within narrowly defined product categories, as expenditure shares and product choices can vary significantly across income groups. He argues for the necessity of using granular data that accurately capture *effective* prices paid, expenditure shares, and the range of products chosen by different income groups, as such detailed data is crucial to accurately identify disparities in inflation rates. In his contribution, Jaravel (2021) identifies what he labels an 'aggregation bias' – a distortion in inflation inequality that arises when this within-category dimension is overlooked. Adopting a similar perspective, Kaplan & Schulhofer-Wohl (2017) provide empirical evidence supporting the

[1] The general inflationary consequences of the Brexit vote, another strand of the literature that we relate to, are discussed in Section 4.3..

significance of accounting for price and product mix variations within narrowly defined product categories. They demonstrate that, when allowing households to pay different prices for identical products and when acknowledging that the assortment of products within product categories can vary across households, the disparity in inflation rates between the lowest and highest income groups in the US from 2004 to 2013 is five times larger compared to a situation where uniform prices are assumed and the same mix of products is used across all households. Consequently, Kaplan & Schulhofer-Wohl (2017) conclude that standard approaches, which presuppose uniform prices and identical product mixes for all households within product categories, fail to capture the heterogeneity in inflation rates.

As more granular data has become increasingly available, recent studies have begun to incorporate the within-category dimension in the estimation of inflation heterogeneity across income groups (Broda & Romalis, 2009, Kaplan & Schulhofer-Wohl, 2017, Jaravel, 2018, Argente & Lee, 2021). A consistent finding emerging from this strand of literature is that poorer households, on average, face significantly higher inflation rates. Various explanations have been proposed to account for this observed inflation inequality. Jaravel (2018) investigates the influence of product innovations on inflation inequality in the United States over the period from 2004 to 2015. He posits that a key driver of this inequality is the accelerated rate of innovation in product categories that are predominantly favored by high-income households. Orhun & Palazzolo (2019) show that liquidity constraints inhibit low-income households from taking advantage of bulk discounts and temporary sales in the US from 2006-2014. Argente & Lee (2021) find that high-income households had lower inflation rates in the US during the Great Recession because they were more able to substitute toward lower-quality products, which have experienced lower price increases.[2]

Another area of literature that our paper engages with concerns the heterogneous price effects of various macroeconomic shocks. Notable studies in this field have examined the impacts of trade liberalization (Porto, 2006, Fajgelbaum & Khandelwal, 2016), monetary policy shocks (Ampudia & Ehrmann & Strasser, 2023) and, most pertinently to our research, the effects of large currency devaluations (Cravino & Levchenko, 2017, Colicev & Hoste & Konings, 2022). A significant focus of the earlier studies has been on understanding how heterogeneity in expenditure shares on product categories generates distributional effects across rich and poor consumers (Porto, 2006, Fajgelbaum & Khandelwal, 2016). Expanding the analytical scope to include the within-category dimension, Cravino & Levchenko (2017) show that heterogeneity in expenditure shares both across and within detailed product categories lead to anti-poor distributional consequences of the 1994 Mexican peso devaluation. They make use of two extremely rich microdata sets. First, on household-level expenditures on detailed product categories, and second, on unique retailer-product level prices. While price data is on a monthly frequency, the expenditure shares are sourced from occasional household surveys, hence they do not account for the possibility that consumers rapidly adjust their spending in response to price shifts. This aspect is considered to be of particular importance in the ongoing literature concerning

[2]Despite several parallels, our analysis differs from the contribution of Argente & Lee (2021) by considering changes in consumption choices following an inflationary shock (and not during a recession), and by putting a stronger emphasis on product-downgrading as a channel of adjustment. It also presents the non-monotonic relationship between income levels and price increases at the product level as a novel finding.

the distributional effects of inflation. Cravino & Levchenko (2017)'s work thus sheds light on the anti-poor consequences of the peso devaluation while also highlighting a critical area for further research: the real-time adaptability of consumption behavior. Colicev & Hoste & Konings (2022), using detailed price and quantity data at the consumer level, study the role of heterogeneity in foreign expenditure shares within a product category and changes in the set of available products before and after the large depreciation of the Kazakh tenge in 2015. They show that heterogeneity in foreign expenditure shares does not lead to important distributional inflation effects. Instead, large changes at the extensive margin and heterogeneity in elasticities of substitution lead to a substantially lower increase in inflation for rich consumers relative to poor consumers. Ampudia & Ehrmann & Strasser (2023) study the effect of monetary policy on the effective inflation rates experienced by low- and high-income earners in euro area countries. They utilize a household panel that captures data on prices and quantities purchased, along with socio-demographic details of the purchasing households, and they highlight product substitution as a key aspect of consumer behavior, with its extent varying between high-income and low-income households. Notably, they observe that inflation experienced by high-income households is more sensitive to monetary policy adjustments, which is attributed to changes in shopping behavior; specifically, following a contractionary monetary policy shock, high-income households tend to increase their shopping intensity compared to low-income households and engage in more pronounced product substitution towards those versions that became relatively cheaper. By contrast, our analysis indicates that, confronted with the inflationary shock in the wake of the Brexit vote, medium-income households were most active in product-downgrading.

We study the distributional effects of the massive depreciation of the British pound in the wake of the June-2016 Brexit vote. The British pound depreciation allows us to examine the distributional effects of foreign exchange shocks on consumer prices in the context of an advanced economy. This is important because existing literature on inflation heterogeneity, driven by exchange rate fluctuations, has been predominantly focused on developing economies. More generally, the body of literature concerning the distributional effects of inflation – e.g., in times of economic downturns as in Argente & Lee (2021) and Coibion & Gorodnichenko & Hong (2015) – has primarily focused on the United States. Our study expands this focus by providing empirical evidence from another advanced economy, the United Kingdom.

We draw on a highly detailed household scanner data set in our analysis. This enables us to apply the key insights from the literature on the distributional effects of inflation. Specifically, we can account for the fact that households may pay different prices for identical items (e.g., a specific gouda cheese from a given brand, identified by a unique product code) and for the real-time variability in the composition of these items within narrowly defined products (e.g., gouda cheese) over time. By comparing volume-share-weighted price averages for different products over time and across households, we can assess how substitution within products impacts inflation rates across income groups. Furthermore, our data set allows us to incorporate the finding that changes in the item availability, such as new introductions and replacements, are important facets for the identification of exchange rate pass-through (Nakamura & Steinsson, 2012, Cavallo & Neiman

& Rigobon, 2014, Goetz & Rodnyansky, 2023, Corsetti et al., 2023). This is particularly relevant in the context of scanner data, in which items keep moving in and out of households' consumption baskets.

Our scanner data set is complemented by a household data file. The availability of this specific socioeconomic data, especially income information, is a rare and advantageous feature of our data set. It empowers us to go beyond a representative agent interpretation and to assess how inflation affects different households across the income distribution. Moreover, we are not constrained to using transaction-level data to categorize consumers into different income groups (see, e.g., Colicev & Hoste & Konings, 2022). Instead, we can directly divide households into seven distinct income groups. This level of granularity goes beyond the typical binary subdivision into 'rich' and 'poor' consumers commonly seen in many studies. Thus, we can investigate potential non-linearities in the heterogeneity of realized inflation across income groups.

## 4.3. The Brexit vote and the depreciation of the British pound

As already noted by Broadbent (2017), the surprising outcome of the Brexit vote in June 2016 triggered a substantial depreciation of the British Pound Sterling. Figure 1 demonstrates that, between June and October 2016, the pound (GBP) lost about 15 percent of its value against the US dollar (USD), the Chinese yuan (CNY) and the Euro (EUR). As for the USD and the CNY, some of this depreciation was reversed in subsequent months. By contrast, the GBP remained persistently cheaper vis-a-vis the EUR.

Not surprisingly, the depreciation resulted in a significant increase in consumer prices, as put forward by Gerstein et al. (2019), Breinlich et al. (2021) and Dhingra & Sampson (2022): first, the drop of the pound's value had a direct effect on the prices of imported goods. Second, increasing prices of imported intermediate inputs raised the costs of British producers, and thus also contributed to rising prices of domestically produced goods (Breinlich et al., 2021). While it is well-known that exchange-rate passthrough into consumer prices is much weaker than passthrough into border prices (Burstein & Gopinath, 2014), the evolution of the British CPI in Figure 2 indicates that consumer prices increased by five percent between mid-2016 and the end of 2017. Figure 2 also shows the evolution of sub-indices of the British CPI, focusing on the type of products that are included in our data set on fast-moving consumer goods (FMCG). With the exception of personal care items, the prices of these goods categories also increased substantially.

Importantly, the depreciation of the GBP in the wake of the Brexit vote was not associated with major macroeconomic turmoil: while financial markets re-assessed their perspective on the UK economy, the UK did not experience an immediate recession or any type of crisis, as evidenced in Figure 3. This distinguishes the Brexit vote-induced depreciation of the British pound from other episodes, which either consider the effects of large depreciations during currency crises (Cravino & Levchenko, 2017) or the evolution of prices during major recessions (Argente & Lee, 2021). This, in turn, implies that both the price changes and the changes in spending patterns that we observe are unlikely to be driven by forces that go beyond the GBP depreciation.

Figure 1: UK Pound sterling exchange rates

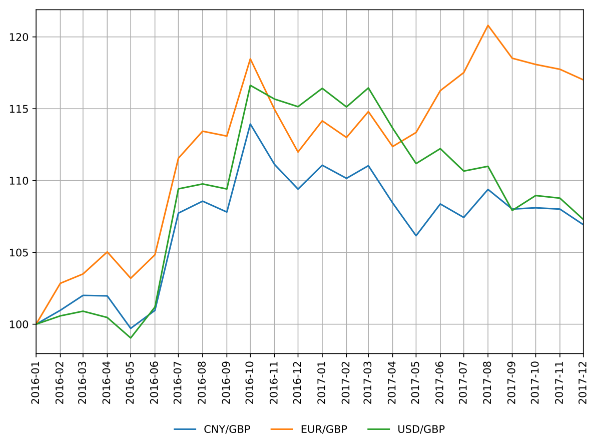
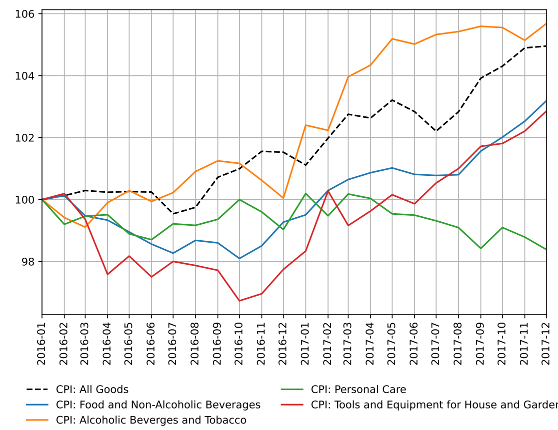



Figure 2: UK prices




**Note:** Figure 1 illustrates a selection of bilateral nominal exchange rates involving the UK Pound sterling. Figure 2 displays price indices in the UK for all goods and specific divisions and subdivisions that closely align with the products encompassed in our scanner data set. Data has been sourced from the UK Office for National Statistics (ONS).

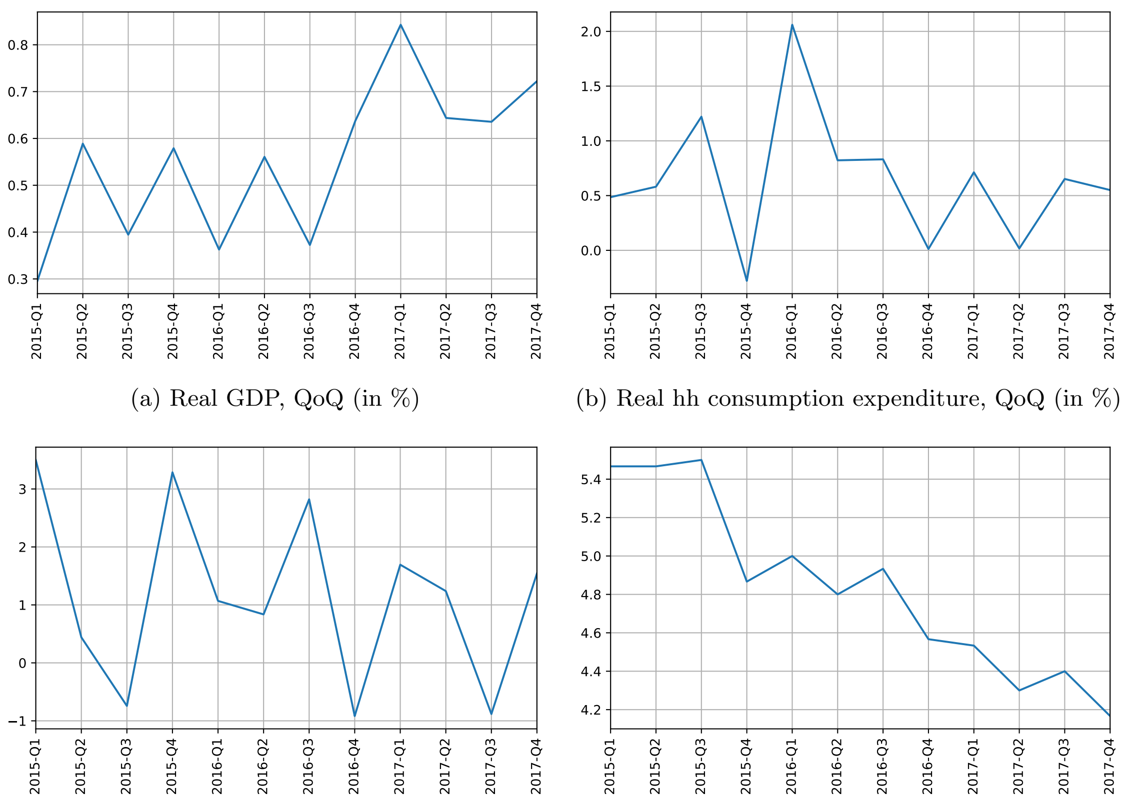
## 4.4. Data set

Our analysis leverages a unique scanner data set in the United Kingdom (UK) spanning the years 2016 and 2017. More specifically, we utilize data from the Kantar Fast-Moving Consumer Goods (FMCG) Purchase Panel, a leading repository for household scanner data. The data set provides detailed transaction information on household purchases of FMCG, which include products typically available in supermarkets, such as food, drinks, alcohol, personal care, household cleaning, cosmetics, etc. Put in the context of the Consumer Price Index (CPI), FMCG predominantly belong to the broad categories *Food and non-alcoholic beverages*, *Alcoholic beverages, Tobacco and narcotics*, *Personal care*, and *Tools and equipment for house and garden*. As per the most recent CPI weights published by the Office for National Statistics (ONS), these four broad categories represent more than 20 percent of total household expenditure in the UK.[3]

The data set provides information on broad product categories (e.g., food and non-alcoholic beverages or personal care), narrower product categories (e.g., dairy products or vegetables), across product types within these categories (e.g., cheese), across products (e.g., gouda cheese) or across items (e.g., a specific gouda cheese from a given brand, identified by a unique code assigned by Kantar). For each transaction, we observe details on (i) the item purchased, (ii) the purchasing household, (iii) the retailer where the transaction took place, (iv) the total transaction value, and (v) the total quantity transacted. These transactional information are supplemented with detailed item characteristics, encompassing the associated product, product type, product category, brand and manufacturer. Additionally, specific attributes, such as volume details, are

[3]It is interesting to compare expenditure on these broad categories over different income groups. As per data extracted from the ONS report on family spending in the UK, in the fiscal year 2015/16, households belonging to the lowest income decile dedicated 17.3 percent of their total expenditure to food and non-alcoholic beverages. In contrast, households belonging to the highest income decile allocated only 7.5 percent of their total expenditure to this broad category. Moreover, it is observed that as one moves down the income distribution deciles, there is a corresponding increase in the proportion of household expenditure allocated to food and non-alcoholic beverages. Accordingly, changes in the prices of these products can disproportionately affect the cost of living of lower-income households.

Figure 3: UK real economy indicators




(a) Real GDP, QoQ (in %)

(b) Real hh consumption expenditure, QoQ (in %)

(c) Real investment, QoQ (in %)

(d) Unemployment rate (in %)

**Source:** International Monetary Fund. All series are seasonally adjusted except for the unemployment rate.

given alongside descriptive information. A sample of these items can be seen in Table 1. It is important to note that the products are defined with a high level of granularity. For example, *Pet Food* is subdivided into type of pet like *Dog*, *Cat*, etc., and further segmented into *Daily Nutrition*, *Treats*, and other types. Similarly, *Soft Drinks* are categorized by taste (e.g., *Bitter Lemon*, *Lemon*, *Cola*, etc.) and by calorie content (*Normal*, *Low Calorie*, etc.). *Beer* is also categorized into different types such as *Lager*, *Pilsner*, *Stout*, etc.

Table 1: Some examples of items in our household scanner data set

| Item Code* | Product Type | Product | Measurement Unit | Volume |
|---|---|---|---|---|
| 6460 | Razor Blades | Double Edge Razor Blades | Piece | 5 in a Pack |
| 7439 | Cat and Dog Treats | Cat Treats | Gram | 55 |
| 9892 | Milk | Semi-Skimmed Milk | Millilitre | 2000 |
| 13239 | Dry Pasta | Dry Pasta Fusilli | Gram | 500 |
| 13953 | Bitter Lemon | Low Calorie Bitter Lemon | Millilitre | 1000 |
| 20582 | Toilet Tissues | Soft Toilet Rolls | Piece | 1 |
| 29915 | Sun Care | Sun Care Aftersun | Millilitre | 400 |
| 40997 | Spirits | Spirits Rum | Millilitre | 1000 |
| 41935 | Nuts | Nuts Snacks | Gram | 50 |
| 43879 | Beer | Stout Beer | Millilitre | 4 X 440 |
| 45950 | Mineral Water | Mineral Water Flavored | Millilitre | 4 X 500 |
| 49278 | Hair Styling Wax | Hair Styling Wax Creams | Gram | 100 |
| 59981 | Cheese | Gouda Cheese | Gram | 200 |
| 63315 | Sugar Confectionery | Sugar Candy | Piece | 50 |
| 69938 | Popcorn | Popcorn Sweet+Savoury | Gram | 30 |
| 70285 | Sugar | Icing Sugar | Gram | 500 |

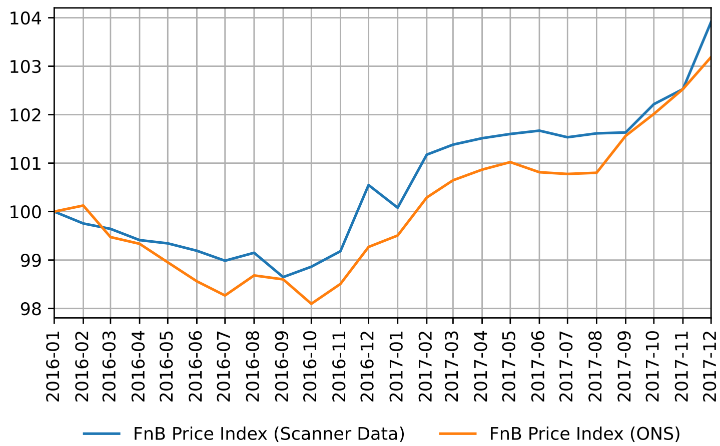
**Note**: The data set also offers information on item name, description, product category, brand and manufacturer. *Item codes are randomized.

Transactions in the data set occur in over 20 unique retailers, ranging from local neighborhood shops to hypermarkets. Retailers are not segmented based on their regional branches or locations; instead, they are aggregated under a unified identifier. For instance, all regional outlets of a specific supermarket chain are collectively treated as a single entity in the data.

To evaluate the accuracy of the scanner data in reflecting price movements, we calculate a Fisher price index for the food and non-alcoholic beverages (FnB) category based on those item-retailer pairs that show transactions throughout 2016 and 2017 on a monthly basis. This index is then compared to the corresponding official price index provided by the ONS in Figure 4. The close alignment of the two time series highlights that the sample of products and prices covered by our scanner data set does not deviate from the sample underlying the official FnB index.

Households in our data set, which serve as the observational panels, are characterized by demographic information sourced from survey questionnaires. For each household, specific attributes, including the annual income and age of the primary earner, as well as household size and the place of residence, are available. The place of residence is determined using the official UK postcode format, established by the General Post Office (Royal Mail). Our dataset includes information on the outward code, specifically the postcode area. The United Kingdom is divided into 124 postcode areas (see Figure 2), which are further subdivided into 2,979 postcode districts.

Figure 4: Food and non-alcoholic beverages price index, ONS and scanner data



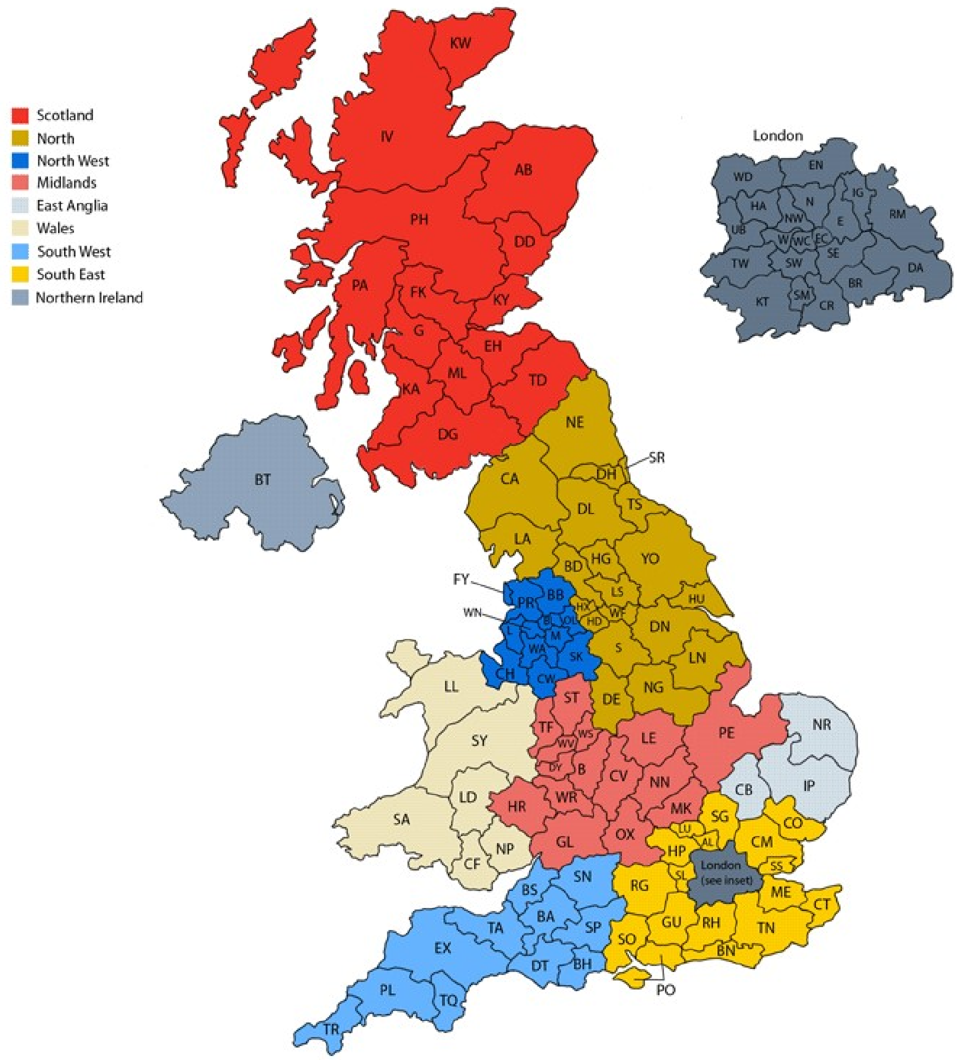

**Note:** This figure illustrates the food and non-alcoholic beverages (FnB) price index derived from scanner data alongside the official FnB index provided by ONS. To construct the scanner data price index, we focus exclusively on item-retailer pairs that show transactions throughout 2016 and 2017 on a monthly basis. This selection ensures the inclusion of items that remain on the market for an extended period. Utilizing this subset, we calculate the cumulative product of the period-on-period Fisher price index, which accounts for both previous and current period expenditures.

With regard to income, Kantar reports that panelists communicate their total labor income before taxes.[4] We utilize Kantar's categorization of households into seven distinct income brackets (in £10,000 increments). Additionally, we apply certain constraints to the households considered in our analysis. First, we keep only those households that report their income either in 2016 or 2017. Second, we include only those households that have consistently reported transactions in every month throughout both 2016 and 2017. This restriction ensures that our results are not distorted by households with specific spending patterns moving into or out of the sample. Third, we restrict our analysis to households that have reported the same postcode in both 2016 and 2017. This criterion is applied to ensure that any variations in expenditure patterns are not influenced by households changing their place of residence. Fourth, our study focuses on households with a size ranging from 1 to 6 members. This range is selected to represent a broad spectrum of household compositions, from single individuals to larger family units, while excluding exceptionally large households that might exhibit atypical consumption behaviors. Fifth, we restrict our analysis to households where the age of the head of the household falls between 18 and 65 years. This age range is chosen to focus on economically active individuals, excluding those typically in full-time education or retirement, as their spending habits may significantly differ from those of the working-age population. Table 3 displays the count of households within each income bracket, complemented by the average household size for each group and the average age of the primary earner. The size of these income groups roughly coincides with the actual UK income distribution, as published by the ONS.[5] Moreover, Figure 5 demonstrates that across most regions, households from all seven income groups are present.

[4]It should be noted that the actual household income may exceed the labor income of the primary earner, encompassing various income streams of different household members.

[5]To compare the distribution of incomes in our sample to the official income distribution, we used Office for National Statistics

Table 2: Map of UK postcode areas




**Source:** www.electricmarketing.co.uk/map-uk-postcodes

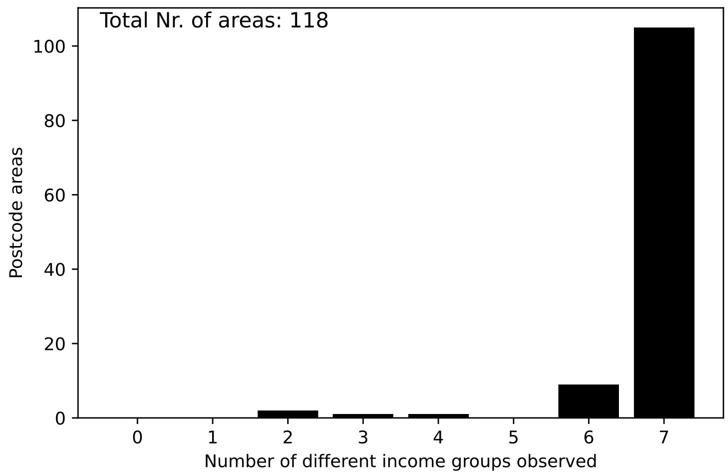
Table 3: Distribution of households by income group

| Income Group | Income Bracket (in GBP) | Number of hh | Mean hh Size | Mean Age of hh Head |
|---|---|---|---|---|
| 1 | up to 9,999 | 716 | 1.97 | 49.19 |
| 2 | 10,000 - 19,9999 | 2,106 | 2.40 | 49.13 |
| 3 | 20,000 - 29,999 | 2,275 | 2.76 | 47.37 |
| 4 | 30,000 - 39,999 | 1,997 | 2.98 | 45.91 |
| 5 | 40,000 - 49,999 | 1,454 | 3.06 | 45.16 |
| 6 | 50,000 - 59,999 | 928 | 3.18 | 43.74 |
| 7 | above 60,000 | 523 | 3.19 | 43.70 |

In our analysis of product-downgrading, we apply two distinct definitions of a *variety*. These approaches incorporate specific criteria including the item code and income group, as well as, potentially, the retailer and

(2023) and deflated nominal income levels by the inflation rate between 2016 and 2022.

Figure 5: Distribution of income groups across postcode areas




postcode area dimensions. Accordingly, a $pi$-variety is defined as a specific item $p$ purchased by households belonging to income group $i \in I$. When incorporating the retailer dimension and the postcode area of the purchasing household, we define a $prai$-variety as a specific item $p$ purchased from retailer $r \in R$ by households residing in postcode area $a \in A$ and belonging to income group $i \in I$.[6] Table 4 provides a summary of the data set, broken down by year. Particularly notable is the high number of products, underscoring the fine granularity with which they are delineated. Furthermore, the table illustrates that a substantial portion of the $pi$- and $prai$-varieties are accompanied by volume information.

Table 4: Summary of the data set by year

| Year | 2016 | 2017 |
|---|---|---|
| Number of Items | 122,689 | 125,221 |
| Number of Retailers | 24 | 24 |
| Number of Areas | 118 | 118 |
| Number of Income Groups | 7 | 7 |
| Number of Product Types | 491 | 487 |
| Number of Products | 1701 | 1678 |
| Number of PRAIs | 6,301,362 | 6,178,300 |
| (of which with Volume Info) | (4,942,730) | (4,464,695) |
| Number of PIs | 627,918 | 632,555 |
| (of which with Volume Info) | (506,197) | (438,058) |
| Sum of Expense (in GBP) | 25,710,009 | 26,005,196 |

**Note:** We adopt a multi-dimensional approach to define a variety, incorporating the item and income group, as well as – potentially – the retailer and postcode area dimension. Accordingly, a $pi$-variety is defined as an item $p$ being purchased by households belonging to income group $i \in I$. When incorporating the retailer dimension and the postcode area of the purchasing household, we define a $prai$-variety as an item $p$ purchased from retailer $r \in R$ by households residing in postcode area $a \in A$ and belonging to income group $i \in I$.

[6] This implies that we incorporate the income group dimension into the definition of a variety. As a consequence, the prices for items sold within the same month, and, potentially, at the same retailer within the same postcode area, can vary across income groups.

## 4.5. Analysis

### 4.5.1. Computing volume-weighted price averages

Our goal is to explore whether – and to what extent – British households cushioned the overall price increase in the wake of the Brexit vote by engaging in *product-downgrading*, i.e. by shifting the composition of their consumption at the product level towards less expensive varieties. Note that this may imply assigning changing weights to varieties purchased in two adjacent periods, but also completely dropping certain varieties from the shopping list or including others that had not been purchased before.

To assess whether average prices paid for a given *variety-mix* within a product differed across income groups and how these differences evolved over time, we start by computing *volume-weighted price averages.* Our data set offers information on unit prices (price per, e.g., gram or milliliter) and on purchased volumes (in, e.g., grams or milliliters) of a *prai*-variety from which we can derive volume-weighted price averages at the *gai-product-group* level. This product group *gai* is defined to include all items $p$ within a specific product $g \in G$, purchased by households living in a specific postcode area $a \in A$ and belonging to a specific income group $i$.[7]

The *volume share* $\mu$ of a specific item-retailer-area-income group combination (i.e. of a *prai*-variety) at a given point in time $t$ within the product $g$ is given by the following expression:

$$\mu^g_{prai,t} = \frac{V_{prai,t}}{\sum_{p \in g} \sum_{r \in R} V_{prai,t}} \tag{1}$$

In (1), $V_{prai,t}$ represents the volume purchased (for instance, in grams or milliliters) of the variety at time $t$. The denominator, $\sum_{p \in g} \sum_{r \in R} V_{prai,t}$, sums the volumes purchased for all items $p$ that belong to product $g$ at time $t$ across all retailers $r$. To illustrate, our approach allows us to calculate the time-dependent volume share of an item $p$, say a specific wheat bread from a given brand, purchased at a specific retailer $r$, within its product $g$ (wheat bread) across all retailers $r$, taking into account both the area $a$ that purchasing households live in and the income group $i$ they belong to.

Following the calculation of volume shares, we proceed to compute the *volume-share-weighted average unit price* $\bar{P}^U$ for each *gai*-product-group at time $t$:

$$\bar{P}^U_{gai,t} = \sum_{p \in g} \sum_{r \in R} (\mu^g_{prai,t} \cdot P^U_{prai,t}) \tag{2}$$

where $P^U_{prai,t}$ is the *unit price* of a variety at time $t$. $\sum_{p \in g}$ and $\sum_{r \in R}$ indicate the summation over all varieties that are part of product $g$ and across all retailers $r$, respectively. As the average unit price is not simply the arithmetic mean, but instead weighted by the volume share of each variety, it is representative

[7]For example, consider a particular *prai*-variety, which could be a specific wheat bread from a given brand (e.g., '$WheatBread_1$') purchased from a specific retailer ('$Retailer_1$') by households living in a particular postcode area ('$Area_1$') and belonging to a specific income group (e.g., the lowest income group). Expanding this concept to the *gai*-product-group, we encompass a range of wheat bread items purchased by members of the lowest income group living in Area 1 at any retailer.

of the actual unit price households of a certain income group living in a certain area pay when purchasing product $g$ (for instance, what lowest income households living in South East London pay for one volume unit of wheat bread). Therefore, each $gai$-product-group in our analysis represents a collection of all items, differentiated by retailer, that belong to the same product, transacted by households from a particular area and income group. We deliberately do not incorporate the retailer dimension in the definition of a product group as we want to allow households to substitute items not only *within* a certain retailer, but potentially also *across* retailers.

The analysis of the following subsections will focus on the question whether the level and evolution of average prices at the product level differed across income groups. Note that the use of *volume shares* allows for a more direct measure of average prices than, e.g., *expenditure weights*, which combine information on both quantities *and* prices and assign greater importance to varieties with higher prices. Of course, volume-share weighting would not be possible if we did not have such granular data, since adding quantities that refer to different products would not make sense.[8]

### 4.5.2. Differences in ***price levels*** across income groups

In this subsection, we demonstrate that the average prices paid by households for the mix of varieties within a given product significantly differ across income groups. Table 5 presents the coefficients of regressing the log of the volume-share-weighted average unit price $\bar{P}^{U}_{gai,t}$ from equation (2) on income group dummies, as well as product, area and time fixed effects, i.e.

$$\ln \bar{P}^{U}_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t} \tag{3}$$

Note that taking the logarithm of price averages transforms absolute differences into percentage deviations, thus addressing the problem that FMCG prices may differ substantially with respect to scale. The product and area dummies make sure that the effect of belonging to a certain income group is not confounded with the effect of consuming specific products or living in a specific area. Finally, the time dummy controls for the overall price increase in the wake of the Brexit depreciation. The estimated coefficients $\beta_i$ thus indicate by how much average prices paid by a representative member of income group $i$ differed from the average prices paid by a representative member of income group 1, which is the omitted category. Figure 6 plots the coefficients displayed in Table 5 with 95-percent confidence intervals. These results indicate that average prices paid by members of the lowest income group are significantly lower than the prices paid by the other income groups. Moreover, average prices paid increase considerably as incomes rise. This suggests that middle-income households purchase a relatively expensive mix of varieties to start with. As a consequence, their consumption bundle exhibits a large scope for within-product adjustment.

[8] Ampudia & Ehrmann & Strasser (2023) also integrate volume-share weighted averages of product prices into their analysis of income group-specific inflation rates.

Table 5: Income groups and price differences at the product level

| | Dependent variable |
|---|---|
| | Log volume-share-weighted average unit price |
| Income Group 2 | 0.022660*** |
| | (0.001782) |
| Income Group 3 | 0.029045*** |
| | (0.002111) |
| Income Group 4 | 0.045516*** |
| | (0.002377) |
| Income Group 5 | 0.062947*** |
| | (0.002694) |
| Income Group 6 | 0.082545*** |
| | (0.002980) |
| Income Group 7 | 0.087880*** |
| | (0.003334) |
| Observations | 6,486,678 |
| Product Fixed Effects | 1,724 |
| Area Fixed Effects | 118 |
| Time Fixed Effects | 24 |
| Adj. R-Squared | 0.835 |
| Standard Errors: Clustered (Product) in Parentheses | |
| ***p<0.01, **p<0.05, *p<0.1 | |

**Note:** We assess whether households with lower incomes tend to purchase more affordable items compared to those with higher incomes. To do so, we regress the log of the volume-share-weighted average unit price $\bar{P}^U_{gai,t}$ from equation (2) on income group dummies, product, area and time fixed effects: $\ln \bar{P}^U_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t}$. The $\beta_i$ coefficients represent the estimated percentage difference in the volume-share-weighted average unit price associated with being in the respective income group $i$ compared to the lowest income group (the reference income group).

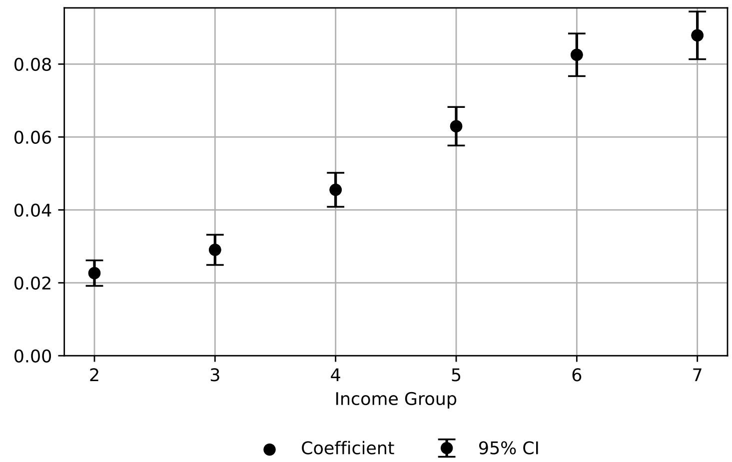
### 4.5.3. Differences in *price changes* across income groups

In a next step, we compute the gross growth rate of the volume-share-weighted average unit price for each $gai$-product-group at time $t$:

$$R^P_{gai,t} = \frac{\bar{P}^U_{gai,t}}{\bar{P}^U_{gai,t-1}} = \frac{\sum_{p \in g} \sum_{r \in R} (\mu_{prai,t} \cdot P^U_{prai,t})}{\sum_{p \in g} \sum_{r \in R} (\mu_{prai,t-1} \cdot P^U_{prai,t-1})} \tag{4}$$

In this equation, $R^P_{gai,t}$ represents a Paasche-type *price relative* for a $gai$-product-group at time $t$. It is derived by dividing the volume-share-weighted average unit price of the current period, $\bar{P}^U_{gai,t}$, by the volume-share-weighted average unit price of the preceding period, $\bar{P}^U_{gai,t-1}$. This approach allows tracing the transition towards other varieties within a $gai$-product-group. For example, if households of a certain income group that live in a certain area start buying more of a cheaper variety of a certain product, this substitution is reflected in the current period's volume shares, and thus, in the calculated $R^P_{gai,t}$. The transition potentially includes substitution among varieties transacted in two adjacent periods $t-1$ and $t$, towards a newly transacted variety in period $t$, and away from a variety transacted in period $t-1$ but not in period $t$. Therefore, this

Figure 6: Income differences and price differences at the product level: Estimated coefficients and 95% CI




**Note:** This figure depicts the $\beta_i$ coefficients and the corresponding 95% confidence intervals when regressing the log of the volume-share-weighted average unit price $\bar{P}^U_{gai,t}$ from equation (2) on income group dummies, product, area and time fixed effects: $\ln \bar{P}^U_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t}$.

approach offers a simple way to deal with *newly transacted* and *discontinued* varieties. The Paasche-type price relative $R^P_{gai,t}$ is representative of the actual gross growth rate of the unit price households from a specific income group and area pay when purchasing one volume unit of product $g$ (for instance, the gross growth rate of what households of a specific income group and area pay for one volume unit of wheat bread).

Table 6 presents the coefficients of regressing the price relative defined in (4) for the $gai$-product-group at time $t$ on income group dummies, product, area and time fixed effects, i.e.

$$R^P_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t} \tag{5}$$

Again, the product group and area dummies account for the correlation between income group-specific and product-specific or area-specific price increases. Moreover, the time dummies capture the overall price increases in the wake of the Brexit depreciation.

Figure 7 plots the coefficients displayed in Table 6 with 95-percent confidence intervals.

The findings displayed in Table 6 and Figure 7 suggest that, controlling for product $g$, area $a$, and time $t$, the price increases experienced by income groups 2 to 4 were significantly lower than the price increases experienced by the lowest income group 1. More specifically, the price increase experienced for a given product g by a member of income group 3 was 0.52 percentage points lower, on average, than the price increase experienced by a member of income group 1 (which is the omitted category). This is not negligible. For income groups 5 to 7, the point estimates are also lower, but not significantly so. These differences may be driven by heterogeneous price increases at the variety level – medium-income households purchasing varieties whose prices change by less – but also by differences in how various income groups adjust their spending patterns – in particular, differences in the extent of product-downgrading. In the following subsections,

Table 6: Income group-specific inflation differences at the product level

| | Dependent variable |
|---|---|
| | $R^P_{gai,t}$ |
| Income Group 2 | -0.004147*** |
| | (0.001009) |
| Income Group 3 | -0.005186*** |
| | (0.001092) |
| Income Group 4 | -0.004891*** |
| | (0.001081) |
| Income Group 5 | -0.001812* |
| | (0.001012) |
| Income Group 6 | -0.000269 |
| | (0.001009) |
| Income Group 7 | -0.000546 |
| | (0.000906) |
| Observations | 4,087,583 |
| Product Fixed Effects | 1,617 |
| Area Fixed Effects | 118 |
| Time Fixed Effects | 23 |
| Adj. R-Squared | 0.008 |
| Standard Errors: Clustered (Product) in Parentheses | |
| ***p<0.01, **p<0.05, *p<0.1 | |

**Note:** We assess whether households with higher incomes tend to experience lower inflation rates compared to those with lower incomes. To do so, we regress the Paasche-type price relative $R^P_{gai,t}$ from equation (4) on income group dummies, product, area and time fixed effects: $R^P_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t}$. The $\beta_i$ coefficients – when multiplied by 100 – represent the percentage-point difference in inflation associated with being in the respective income group $i$ compared to the lowest income group (the reference income group). Note that after having created the price relatives, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

we will explore to what extent changes in the variety-mix at the product-level contributed for the results displayed in Table 6 and Figure 7.

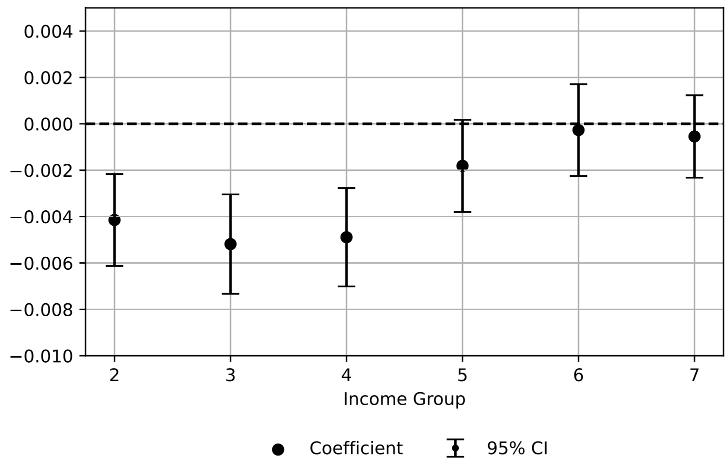
#### 4.5.4. Identifying the role of product-downgrading: Comparing Laspeyres and Paasche indices

In order to assess how much households' adjusting of the variety-mix at the product level contributed to differences in income group-specific inflation rates, we compare Laspeyres-type price relatives to Paasche-type price relatives. As we will show below, this allows quantifying the price increase that households would have experienced without an adjustment of the variety mix.[9]

To achieve this goal, we aggregate unit price levels at the $gi$-product-group level and then compute their period-on-period changes over time using two different weighting schemes. The primary reason for excluding the retailer and area dimensions from the definition of a variety is that that aggregating over retailers and

[9] Ampudia & Ehrmann & Strasser (2023) follow a similar approach to assess the relevance of different margins of adjustment in generating heterogenous inflation rates.

Figure 7: Income group-specific inflation differences at the product level: Estimated coefficients and 95% CI




**Note:** This figure depicts the $\beta_i$ coefficients and the corresponding 95% confidence intervals when regressing the Paasche-type price relative $R^P_{gai,t}$ from equation (4) on income group dummies, product, area and time fixed effects: $R^P_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t}$. Note that after having created the price relatives, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

areas significantly reduces fluctuations in the monthly purchasing sample over time; while the *prai*-variety could be a specific wheat bread from a given brand purchased from a specific retailer by households living in a particular postcode area and belonging to a specific income group, the *pi*-variety would just depict a specific wheat bread from a given brand purchased by households belonging to a specific income group. Consequently, the majority of *pi*-varieties are purchased in two adjacent periods. More specifically, approximately 85 percent of total expenditure is allocated to those *continued pi*-varieties, thereby diminishing the importance of the extensive margin – i.e., newly transacted and discontinued varieties. This allows restricting the data set to a sub-sample of continued *pi*-varieties and facilitates the comparison of period-on-period inflation rates based on Paasche and Laspeyres indices without sacrificing a significant number of observations.

The average unit *price relative* for each *gi*-product-group at time $t$, utilizing a weighting scheme based on the volume shares from the *previous* period, is given by:

$$R^L_{gi,t} = \frac{\sum_{p \in g} (\mu_{pi,t-1} \cdot P^U_{pi,t})}{\sum_{p \in g} (\mu_{pi,t-1} \cdot P^U_{pi,t-1})} \tag{6}$$

In this equation, $R^L_{gi,t}$ represents the *Laspeyres*-type price relative for the *gi*-product-group at time $t$. The numerator gives the volume-share-weighted average unit price of all *pi*-varieties within the *gi*-product-group at time $t$, each weighted by its respective *previous*-period volume share, defined as $\mu_{pi,t-1} = \frac{V_{pi,t-1}}{\sum_{p \in g} V_{pi,t-1}}$. The denominator depicts the volume-share-weighted average unit price of all *pi*-varieties within the *gi*-product-group at time $t-1$, each weighted by its volume share in perod $t-1$ This Laspeyres-type calculation gives us an insight into how the prices would have changed over time if the consumption pattern (in terms of volume distribution among varieties) had remained stable. As it relies on the consumption pattern of the previous period, it does not incorporate substitution within the $gi$-product-group that may have occurred in the current period. Note that if a variety was purchased in period $t-1$ but not in period $t$, it does not have a unit price $P^U_{pi,t}$ in period $t$. These varieties are referred to as *discontinued* varieties because they were purchased in the previous period but are no longer available or relevant in the current period. If a variety was purchased in period $t$ but not in period $t-1$, its volume share $\mu_{pi,t-1}$ would be zero in period $t-1$. These varieties are referred to as *newly transacted* varieties because they were not available or relevant in the previous period but are purchased in the current period. As both discontinued and new varieties impede the computation of $R^L_{gi,t}$, they are removed from the sample and we restrict our attention to those varieties that are transacted in two adjacent periods, i.e. to the sub-sample of *continued* varieties. As mentioned above the aggregation over areas and retailers guarantess that a large share of varieties is continued at each point in time.

In order to assess the extent of substitution within products, we also compute Paasche-type price relatives, which are given by the average unit price relative for each $gi$-product-group at time $t$ and $t-1$, weighted by the respective *current* period's volume shares:

$$R^P_{gi,t} = \frac{\bar{P}^U_{gi,t}}{\bar{P}^U_{gi,t-1}} = \frac{\sum_{p\in g}(\mu_{pi,t} \cdot P^U_{pi,t})}{\sum_{p\in g}(\mu_{pi,t-1} \cdot P^U_{pi,t-1})} \tag{7}$$

Note that this approach allows tracing the shift of volume shares within a $gi$-product-group. For example, if consumers start buying more of a cheaper variety within a certain $gi$-product-group, this substitution is reflected in the current period's volume shares, and thus, in the calculated $R^P_{gi,t}$. To retain the same sub-sample of varieties as in the Laspeyres-type price relatives, we keep our attention limited to the sub-sample of continued varieties.

The difference between the Laspeyres- and Paasche-type price relatives, which quantifies the extent to which the inflation rate for a $gi$-product-group is influenced by substitution within that $gi$-product-group in the specified time period, is computed as:

$$\Delta\hat{P}_{gi,t} = R^L_{gi,t} - R^P_{gi,t} \tag{8}$$

Note that we can rewrite (8) as

$$\Delta\hat{P}_{gi,t} = \frac{\sum_{p\in g}(\mu^g_{pi,t-1} - \mu^g_{pi,t}) \cdot P^U_{pi,t}}{\bar{P}^U_{gi,t-1}} \tag{9}$$

The value yielded by (9) is high if, on average, households *reduce* the volume share of varieties within a $gi$-product-group that are *expensive* in period $t$. The volume-weighted average in the denominator ($\bar{P}^U_{gi,t-1}$) serves as a scaling variable, which makes sure that $\Delta\hat{P}_{gi,t}$ is comparable across products, and that the expression is not dominated by a few high-price products. Note that (9) stands in contrast to approaches that focus on households substituting away from varieties whose prices *grow* at a higher rate.[10] A simple example illustrates the case: suppose that a household from a certain income group has access to two items within a product, with the first one initially costing one monetary unit and the second one two monetary units. In period $t-1$, the household primarily purchases the expensive item. Between period $t-1$ and period $t$, *both* prices increase by ten percent, and the household reacts by switching in parts from the expensive to the inexpensive item. This would not be detected in an analysis concentrating on growth rates, since both items' prices increase by the same percentage. By contrast, equation (9) would yield a positive value, indicating some product-downgrading.

To explore whether the extent of product-downgrading differs across different income groups, we estimate the parameters of the following regression equation:

$$\Delta \hat{P}_{gi,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \gamma_t + \epsilon_{gi,t} \tag{10}$$

As before, $\text{Income\_Group}_i$ is a dummy variable with the subscript starting from 2 because income group 1 is the omitted reference group. $\delta_g$ and $\gamma_t$ are product and time fixed effects, respectively. The results of estimating this regression are presented in Table 7. Furthermore, Figure 8 illustrates the estimated coefficients along with their respective 95-percent confidence intervals. The results indicate that the middle-income groups engage significantly more in product-downgrading than both the lowest and highest income groups. More specifically, relative to income group 1, the ability or willingness to adjust the mix of varieties lowers the average product-specific inflation rate by 0.25 percentage points for members of income group 2.

### 4.5.5. Identifying the role of product-downgrading: The role of the extensive margin

While comparing Laspeyres and Paasche inflation at the *gi*-product-group level yields important insights on the extent of product-downgrading across income groups, this approach comes with at least three drawbacks. First, the exclusion of regional and retailer-specific price effects may influence the results. In other words, factors attributed to income group dynamics may actually be influenced by the omitted retailer or area dimensions. For instance, if lower-income households predominantly reside in rural areas, and if price dynamics in rural areas significantly differ from those in urban areas, inflation differentials may be misinterpreted as being driven by the income group rather than the location. Similarly, if lower-income households mainly shop at discount retailers, and if price dynamics in these stores significantly differ from other types of retailers, inflation differentials may be incorrectly attributed to the income group rather than retailer type. Second, the inability to identify the role of the extensive margin in driving inflation differentials arises from the reliance on a sub-sample of continued varieties – which is, however, large if we aggregate across areas and retailers..

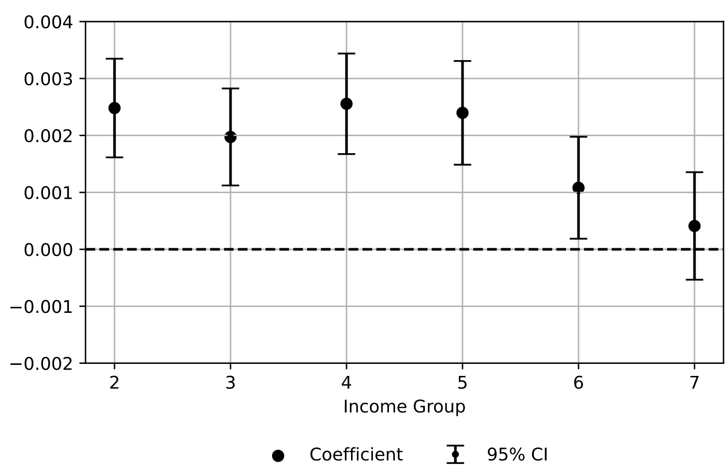
[10] When considering the role of quality substitution, Argente & Lee (2021) focus on the substitution from products with higher price growth rates towards products with lower price growth rates.

Table 7: The difference between Laspeyres vs. Paasche inflation on the product level – continued *pi*-varieties

| | Dependent variable |
|---|---|
| | $\Delta\hat{P}_{gi,t}$ |
| Income Group 2 | 0.002481*** |
| | (0.000442) |
| Income Group 3 | 0.001973*** |
| | (0.000434) |
| Income Group 4 | 0.002556*** |
| | (0.000450) |
| Income Group 5 | 0.002397*** |
| | (0.000464) |
| Income Group 6 | 0.001081** |
| | (0.000456) |
| Income Group 7 | 0.000410 |
| | (0.000481) |
| Observations | 195,625 |
| Product Fixed Effects | 1,656 |
| Time Fixed Effects | 23 |
| Adj. R-Squared | 0.003 |
| Standard Errors: Clustered (Product) in Parentheses | |
| ***p<0.01, **p<0.05, *p<0.1 | |

**Note:** This table shows the results of regressing the difference between the Laspeyres- and Paasche-type price relatives $\Delta\hat{P}_{gi,t}$ on income group dummies, product and time fixed effects. Note that after having computed $\Delta\hat{P}_{gi,t}$, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

Figure 8: The difference between Laspeyres vs. Paasche inflation on the product level – continued *pi*-varieties: Estimated coefficients and 95% CI




**Note:** This figure depicts the $\beta_i^{\Delta}$ coefficients and the corresponding 95% confidence intervals when regressing the difference between the Laspeyres- and Paasche-type price relatives $\Delta\hat{P}_{gi,t}$ on income group dummies, product and time fixed effects: $\Delta\hat{P}_{gi,t} = \sum_{i=2}^{I} \beta_i^{\Delta} \cdot \text{Income\_Group}_i + \delta_g + \gamma_t + \epsilon_{gi,t}$ Note that after having computed $\Delta\hat{P}_{gi,t}$, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

Lastly, what may initially appear as a continued variety under the *pi*-definition of a variety could actually be a newly transacted variety under the *prai*-definition of a variety. In other words, when a specific item is purchased in two adjacent periods by households within a particular income group across various retailers and postcode areas, we cannot be sure that it was part of the same income group's consumption basket in the previous period within a specific retailer and postcode area. Therefore, the inclusion of the retailer and postcode area dimensions, despite increasing fluctuations in the purchasing sample over time, enables us to account for location and retailer effects and identify extensive margin effects more clearly. Since it is not possible to compare period-on-period inflation indices based on previous period volume weighting and current period volume weighting for each *prai*-variety, we propose an alternative strategy to explain inflation differentials across income groups.

We begin by analyzing the *continued prai*-varieties sub-sample, whereby we replicate the computation of volume shares $\mu^{g,cont}_{prai,t}$ and volume-share-weighted average unit prices $\bar{P}^{U,cont}_{gai,t}$, as described in equations (1) and (2), respectively. Following this, we compute the average unit price relative for each *gai*-product-group at time $t$:

$$\dot{R}^{P}_{gai,t} = \frac{\bar{P}^{U,cont}_{gai,t}}{\bar{P}^{U,cont}_{gai,t-1}} \tag{11}$$

Subsequently, we repeat the regression analysis in which we regress this price relative on income group dummies, product, area, and time fixed effects, akin to the procedure outlined in equation (5):

$$\dot{R}^{P}_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t} \tag{12}$$

The results of this regression are presented in Table 8. Furthermore, Figure 9 illustrates the estimated coefficients along with their respective 95-percent confidence intervals.

The result that there are no inflation differences between income groups when only *continued* varieties are considered (see Figure 9), but that such differences exist when we include all varieties (see Figure 7) suggests that the differences are driven by the discontinued and newly transacted varieties. This indicates that a shift in the *variety-mix* at the *extensive margin* – which includes changes in the item $p$ and/or retailer $r$ – is key to understanding the observed inflation disparities.

To further corroborate this finding, we compute the previous-period volume shares $\mu^{g,discont}_{prai,t-1}$ and volume-share-weighted average unit prices $\bar{P}^{U,discont}_{gai,t-1}$ based on the sub-sample of *discontinued prai*-varieties. Next, we compute the average unit price of *all prai*-varieties in period $t$ relative to the discontinued *prai*-varieties in period $t-1$ for each *gai*-product-group:

$$\tilde{R}^{P}_{gai,t} = \frac{\bar{P}^{U}_{gai,t}}{\bar{P}^{U,discont}_{gai,t-1}} \tag{13}$$

The ratio $\tilde{R}^{P}_{gai,t}$ compares the average unit price of all varieties in period $t$ to the average unit price of discontinued varieties in the previous period $t-1$. The *more expensive* the discontinued varieties are in

Table 8: Inflation disparities on the product level – continued *prai*-varieties

| | Dependent variable |
|---|---|
| | $R^{P,cont}_{gai,t}$ |
| Income Group 2 | 0.000456* |
| | (0.000271) |
| Income Group 3 | 0.000359 |
| | (0.000266) |
| Income Group 4 | 0.000383 |
| | (0.000267) |
| Income Group 5 | 0.000303 |
| | (0.000274) |
| Income Group 6 | 0.000174 |
| | (0.000296) |
| Income Group 7 | 0.000130 |
| | (0.000328) |
| Observations | 2,391,455 |
| Product Fixed Effects | 1,606 |
| Area Fixed Effects | 118 |
| Time Fixed Effects | 23 |
| Adj. R-Squared | 0.002 |
| Standard Errors: Clustered (Product) in Parentheses | |
| ***p<0.01, **p<0.05, *p<0.1 | |

**Note:** We assess whether households with higher incomes tend to experience lower inflation rates compared to those with lower incomes within the continued *prai*-varieties sub-sample. To do so, we regress the unit price relative $R^{P,cont}_{gai,t}$ on income group dummies, product, area and time fixed effects: $R^{P,cont}_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t}$. The $\beta_i$ coefficients – when multiplied by 100 – represent the percentage-point difference in inflation associated with being in the respective income group $i$ compared to the lowest income group (the reference income group). Note that after having created the price relatives, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

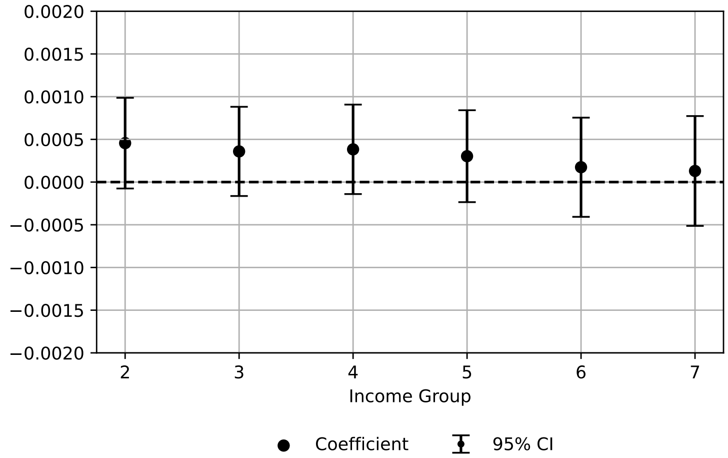
period $t-1$, the *lower* is the ratio $\tilde{R}^P_{gai,t}$. If we find that $\tilde{R}^P_{gai,t}$ significantly differs across income groups (controlling for products, areas, and time), this indicates that income groups differ in the extent to which they drop expensive varieties from their consumption basket.

Similarly, using the *newly transacted prai*-varieties sub-sample, we compute the current period volume shares $\mu^{g,new}_{prai,t}$ and volume-share-weighted average unit prices $\bar{P}^{U,new}_{gai,t}$. Subsequently, we compute the average unit price of new *prai*-varieties in period $t$ relative to all *prai*-varieties in period $t-1$ for each *gai*-product-group:

$$\hat{R}^P_{gai,t} = \frac{\bar{P}^{U,new}_{gai,t}}{\bar{P}^{U}_{gai,t-1}} \tag{14}$$

The ratio $\hat{R}^P_{gai,t}$ serves as a comparison between the average unit price of newly transacted varieties in period $t$ and the average unit price of all varieties in the previous period $t-1$. The *less expensive* the newly transacted varieties are in period $t$ relative to the average unit price based on all varieties in period $t-1$, the *lower* is the ratio $\hat{R}^P_{gai,t}$. Significant differences of this ratio across income groups indicate differences in the extent to which households newly include less expensive varieties in their consumption basket.

Figure 9: Inflation disparities on the product level – continued *prai*-varieties: Estimated coefficients and 95% CI




**Note:** This figure depicts the $\beta_i$ coefficients and the corresponding 95% confidence intervals when regressing the Paasche-type price relative $R^{P,cont}_{gai,t}$ on income group dummies, product, area and time fixed effects: $R^{P,cont}_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t}$. Note that after having created the price relatives, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

To identify possible differences across income groups, we regress the above price relatives on income group dummies, product, area, and time fixed effects:

$$\tilde{R}^P_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t} \tag{15}$$

and

$$\hat{R}^P_{gai,t} = \sum_{i=2}^{I} \beta_i \cdot \text{Income\_Group}_i + \delta_g + \sigma_a + \gamma_t + \epsilon_{gai,t} \tag{16}$$

The regression results are presented in Table 9, while Figure 10 shows the resulting coefficients along with their respective 95-percent confidence intervals. The table and figure demonstrate that adjustments at the extensive margin play a significant role in explaining the inflation disparities across income groups, as depicted in Figure 7. Additionally, the significantly negative coefficients in column 1 of Table 9 suggest that (complete) substitution away from expensive varieties constitutes the primary channel of adjustment. Again, it is members of the *medium-income* groups for whom this effect is most pronounced, i.e. for whom average prices for a product relative to the average price of discontinued varieties is lowest, which indicates that these households are most effectively engaged in product-downgrading.

## 4.6. Summary and conclusions

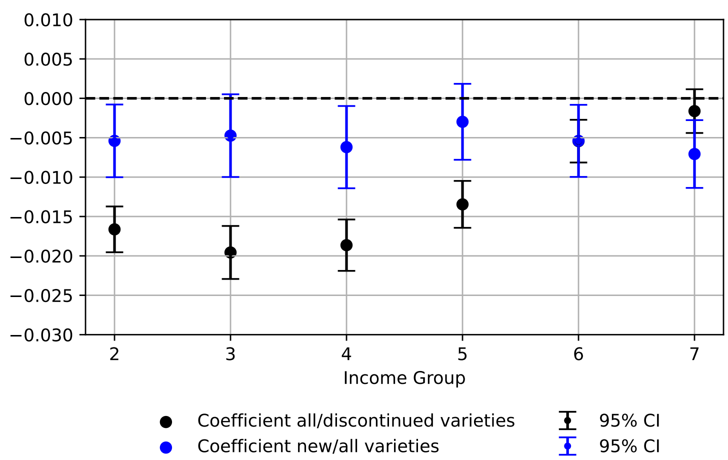
In this paper, we have focused on the role of *product-downgrading* as one particular mechanism, due to which different income groups may experience different effective inflation rates, and which may thus contribute to

Table 9: Inflation disparities at the product level – discontinued and new *prai*-varieties

| | Dependent variable | |
|---|---|---|
| | $\tilde{R}^{P}_{gai,t}$ | $\hat{R}^{P}_{gai,t}$ |
| Income Group 2 | -0.016631*** | -0.005399** |
| | (0.001482) | (0.002352) |
| Income Group 3 | -0.019566*** | -0.004735* |
| | (0.001715) | (0.002677) |
| Income Group 4 | -0.018640*** | -0.006195** |
| | (0.001663) | (0.002661) |
| Income Group 5 | -0.013460*** | -0.002980 |
| | (0.001518) | (0.002458) |
| Income Group 6 | -0.005436*** | -0.005400** |
| | (0.001382) | (0.002332) |
| Income Group 7 | -0.001622 | -0.007069*** |
| | (0.001415) | (0.002193) |
| Observations | 3,329,896 | 3,308,937 |
| Product Fixed Effects | 1,470 | 1,468 |
| Area Fixed Effects | 118 | 118 |
| Time Fixed Effects | 23 | 23 |
| Adj. R-Squared | 0.007 | 0.019 |
| Standard Errors: Clustered (Product) in Parentheses | | |
| ***p<0.01, **p<0.05, *p<0.1 | | |

**Note:** This table shows the results of regressing the unit price relatives $\tilde{R}^{P}_{gai,t}$ and $\hat{R}^{P}_{gai,t}$ on income group dummies, product, area and time fixed effects. Note that after having created the price relatives, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

Figure 10: Inflation disparities at the product level – discontinued and new *prai*-varieties: Estimated coefficients and 95% CI




**Note:** This figure depicts the $\beta_i$ coefficients and the corresponding 95% confidence intervals when regressing the unit price relatives $\tilde{R}^{P}_{gai,t}$ and $\hat{R}^{P}_{gai,t}$ on income group dummies, product, area and time fixed effects Note that after having created the price relatives, we have excluded the 1st and 99th percentiles to mitigate the effect of outliers.

the distributional effects of inflation: households who are able and willing to replace more expensive varieties of a given product by less expensive alternatives cushion the impact of the overall price increase. Conversely, households who are unable or unwilling to do so – either because their initial consumption basket already consists of the cheapest varieties, or because their income allows them to stick to the previous spending pattern – experience higher effective inflation rates. The granular data set of household-level purchases of fast-moving consumer goods allows tracing the level and evolution of volume-share-weighted price averages for a large number of detailed products, and thus to precisely identify the extent of product-downgrading for different income groups.

Focusing on the evolution of prices in the United Kingdom shortly before and after the depreciation of the British pound in the wake of the Brexit referendum, we have come up with the following results: first and not surprisingly, the average unit price paid for a given product increases in households' income. Second, and more importantly, the relationship between product-specific inflation rates and income levels exhibits a U-shaped pattern: while medium-income households experience significantly lower price increases than low-income households, there is no significant difference between high-income and low-income households.

To demonstrate the relevance of product-downgrading for different effective inflation rates across income groups, we computed the differences between Laspeyres- and Paasche-type price relatives, thus juxtaposing the price evolution without and adjustment of the variety mix with an evolution that allows for substitution. We also demonstrated that income groups differ in the extent to which the average price of discontinued varieties relates to the average price of all varieties consumed and to which the average price of newly transacted varieties differs from the average price of all varieties consumed in the previous period. Our findings suggest that it is medium-households' ability or willingness to completely remove expensive varieties from their product mix, which gives rise to the observed pattern of product-downgrading.

Hence, from this perspective, inflation is both anti-poor *and* anti-rich – but, of course, for different reasons: while the scope for product-downgrading is limited for poor households, who already consume the lowest-priced varieties to start with, rich households' reluctance to switch to less expensive varieties may reflect their ability to afford the price increase. In contrast to households at the lower and upper ends of the British income distribution, those in the middle seem to take advantage of the possibility to engage in product-downgrading and to thus cushion the effect of the overall price increase. We are, of course, aware, that the observation of lower effective inflation rates for these groups does not exhaust all the welfare effects of the "Brexit inflation": any substitution – be it across or within products – potentially reduces the utility of consumers who replace components of their favored consumption bundle by possibly *inferior* items. However, we point out that the varieties we consider are almost perfect substitutes in terms of nutritional value, cleaning performance etc. – i.e. the welfare effects of substituting varieties within those products are likely to be rather small, and essentially reflect the *brand value* of more expensive varieties.[11]

Finally, we emphasize that our paper focused on *one* aspect that may potentially contribute to heteroge-

[11] This is also the reason why we preferred to use the term *product-downgrading* instead of *quality adjustment*, referred to by, e.g., Argente & Lee (2021).

neous effects of inflation – namely, substitution within narrowly defined products. We are aware that these effects are augmented by other sources of heterogeneity – most importantly, different *expenditure shares* and different elasticities of substitution *across* products. However, we believe that the results we have presented add an important insight on the distributional effects of inflation, which – for lack of appropriate data – had to be neglected so far.

# 5. Retail prices during the 2014-2015 US dollar rally: a microscopic perspective using scanner data

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February 2024

**Abstract**

In the second half of 2014, the US dollar appreciated substantially and persistently against most other currencies in the world. The appreciation reflected market expectations of a tighter monetary policy and accelerating growth in the US, and was not related to specific events in individual countries. We focus on this episode to analyze the effects of exchange rate movements on domestic prices, i.e. the extent of exchange rate pass-through. Using scanner data on retail prices of fast-moving consumer goods in Brazil, Chile, Colombia, Mexico and Peru, we document the following findings: during the dollar rally, retail prices of imported goods (”imported products”) increased, but the increase was delayed and muted. More importantly, retail prices of domestically produced goods (”domestic products”) moved in parallel to the prices of imported products of the same product category, such that relative prices of imported products vis-á-vis their domestic substitutes barely changed. Our results suggest that the role of the retail sector goes beyond a mere ”buffer”, which dampens the effect of exchange rate fluctuations on relative prices. As a consequence, we conjecture and show that – after a depreciation of the domestic currency – expenditure switching from imported to domestic products is much weaker than generally believed.

**Keywords**

Exchange Rate Pass-through, Scanner Data, Dominant Currency Paradigm

**JEL-Codes**

E31 · F31 · F41 · L81

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## 5.1. Introduction

In times of high inflation rates, it is important to identify the forces behind rising consumer prices. One prominent candidate are exchange rate fluctuations, with a depreciation of the domestic currency potentially raising domestic prices of imported products if foreign producers fix their prices in their own currency. The rising price of imported products possibly induces consumers to shift their spending to domestically produced substitutes, whose prices are not directly affected by the exchange rate. However, the extent of expenditure switching may be limited by low elasticities of substitution, or by the lack of domestic products that serve the same purpose as imports. Hence, despite its effect on relative prices, a depreciation is likely to raise the overall price level.

Of course, this narrative about the effect of exchange rate fluctuations on domestic prices – i.e. the extent of exchange rate pass-through (ERPT) – is based on a whole range of assumptions, which may be violated in practice: first, foreign exporters may fix their prices in the currency of the importing country ("local currency pricing"), such that, at least in the short run, domestic prices are immune to exchange rate fluctuations. Second, the prices of domestically produced products ("domestic products") may also increase, due to the higher costs of imported raw materials and intermediate inputs. Finally, price reactions at the retail level may differ from price reactions at the border, with the "retail wedge" substantially dampening the effect of exchange rate fluctuations. Given the resulting ambiguities in the exchange rate-inflation nexus, it is not surprising that a large literature explores the extent and dynamics of ERPT.

Our paper contributes to this literature in the following way: We focus on the "US dollar (USD) rally" that started in mid-2014, and that resulted in a substantial nominal appreciation of the US dollar against most other currencies in the world. This appreciation was driven by markets' expectations of a tighter monetary policy and accelerating growth in the US, and thus exogenous to the countries whose currencies were affected. To explore the effects of the US dollar rally on prices, we use a detailed household scanner data set on "fast-moving consumer goods" (FMCG) – i.e., food and non-alcoholic beverages, as well as personal care and household items. The focus on individual products (rather than highly aggregated price indices) comes with several advantages: first, we are able to separate price movements from changes in spending patterns. Second, we can distinguish between imported products and domestically produced goods ("domestic products") of the same product category, i.e. close substitutes whose prices should not be directly affected by developments on foreign exchange markets. While we believe that our analysis is of general relevance, we focus on Colombia and four other Latin American countries (Brazil, Chile, Mexico and Peru) since the overwhelming share of these countries' imports are priced in US dollars – i.e. prices of imported products should have been affected particularly strongly by the US dollar rally.

We started our analysis with the expectation that the massive appreciation of the US dollar against the Colombian peso (COP) should have left its trace in Colombian retail prices, and that – at least in the short run – the prices of imported products should have moved more strongly than the prices of domestic products of the same product category. Interestingly, this is not what we found: the price reaction to the US dollar rally was delayed and muted. More specifically, it took about six months until price indices of imported products started to increase, and the mild increase in prices of a few percent pales against the depreciation of the Colombian peso against the US dollar by 40 percent. Moreover, and even more surprisingly, we found that prices of imported products and of domestic products of the same product category – i.e. domestically produced close substitutes – moved in parallel, such that the ratio of imported product prices over domestic product prices barely changed. The parallel evolution of similar imported and domestic products suggests a role of the retail sector that is much more active than generally believed. Moreover, due to the absence of relative price changes we should not expect a considerable shift of consumers' spending from imported to domestic products. Our analysis of (aggregate) expenditure switching and (disaggregate) quantity reactions supports this conjecture.

The rest of this paper is structured as follows: In Section 5.2., we outline the basic argument and relate our work to the existing literature on exchange rate pass-through. In Section 5.3., we discuss the global US dollar rally and the macroeconomic environment in Colombia. The initial focus on this country is justified by two considerations: First, the depreciation of the Colombian peso against the US dollar was particulalry strong in the second half of 2014 and first quarter of 2015. Second, the macroeconomic situation in Colombia was free of turbulences, justifying the "event-study approach" that we adopt. Section 5.4. presents our data set. Section 5.5. describes our empirical approach and presents our results for Colombia. Section 5.6. focuses on the robustness of the Colombian-specific findings and extends the analysis to Brazil, Chile, Mexico and Peru. Section 5.7. offers a summary and some conclusions.

## 5.2. Conceptual foundations and relevant literature

Most analyses of ERPT start from the simple hypothesis that, with foreign (F) exporters fixing the price of good $i$ in their own currency ($P_{i,t}^{F}$), the domestic (H) currency-price of this good ($P_{i,t}^{H}$) should be given by:

$$P_{i,t}^{H} = E_t \cdot P_{i,t}^{F} \tag{1}$$

where $E_t$ is the domestic currency-price of the foreign currency. That is, the *law of one price* (LOP) should prevail, and a change in the nominal exchange rate should be reflected by a change in the domestic price of the same percentage, i.e. $\Delta p_{i,t}^{H} = \Delta e_t$, with lower-case letters denoting the natural logarithm of variables. If foreign producers do not adhere to *producer currency pricing* (PCP), but fix their prices in a "vehicle currency", e.g. the US dollar, the same logic applies. In this case, however, the relevant exchange rate is not the relative price of the exporter's currency in terms of the importer's currency, but the exchange rate of the importer with respect to the vehicle currency. Recent research highlights the pervasive role of the US dollar and of *dominant currency pricing* (DCP).[1]

There are numerous reasons why "full ERPT" may not be observed in reality: First, producers may fix

[1] See, e.g., Boz & Gopinath & Plagborg-Møller (2017), Gopinath et al. (2020), Gopinath & Itskhoki (2021), Boz et al. (2022).

prices in the importers' currency. In this case of *local currency pricing* (LCP), domestic prices are immune to exchange rate fluctuations – at least in the short run. Moreover, while prices "at the dock" – so-called *border prices* – may react very strongly to exchange rate fluctuations, *retail prices* combine border prices and the price of (non-traded) distribution services, which reflect the costs of moving goods from the border to the store shelf, the market structure in the domestic retail industry, etc. One should therefore expect retail prices to be much less responsive to exchange rate fluctuations than border prices. For the same reason, the consumer price index (CPI), which represents a weighted average of individual goods' prices at the retail level, should be less affected by the exchange rate than an import price index. This is, in fact, what the literature finds. As reported in the survey by Burstein & Gopinath (2014), "ERPT into consumer prices is lower than into border prices" (p.401).

Many studies that explore ERPT into price aggregates (see, e.g., Campa & Goldberg, 2005) or individual goods prices (see, e.g., Frankel & Parsley & Wei, 2011) regress changes of domestic prices on exchange rate changes at various lags, possibly applying a (vector) error correction specification. While this allows tracing the extent of ERPT over time, it comes with the problem that exchange rates may as much be driven by domestic price movements as prices by exchange rates – i.e. it is hard to identify causal relationships. To address this shortcoming, several contributions adopt an "event-study" design, which observes the evolution of domestic prices shortly before and after an exogenous – and often sizable – move of the exchange rate. In this vein, Burstein & Eichenbaum & Rebelo (2005) analyze the reaction of domestic prices during currency crises episodes. Bonadio & Fischer & Sauré (2019) as well as Auer & Burstein & Lein (2021) consider the behavior of prices in Switzerland in the wake of the massive appreciation of the Swiss franc in early 2015. Finally, Breinlich et al. (2021) focus on prices in the United Kingdom after the Brexit-induced depreciation of the British pound.

Our paper contributes to this literature in the following way: We consider the effects of the "US dollar rally" of 2014-2015, which originated in changing expectations about future US monetary policy. While this change in expectations resulted in a strong (and exogenous!) appreciation of the US dollar vis-á-vis most currencies in the world, it did not come with the usual financial and economic turbulences that characterize most currency crises. Using an event-study design, we analyze prices of (and expenditures on) a large number of goods at the retail level. The granular nature of our data set allows juxtaposing the prices of imported and domestic products. This makes it possible to analyze whether the prices of imported products reacted more strongly to the depreciation of the domestic currency – in our case: the Brazilian real (BRL), Chilean peso (CLP), Colombian peso (COP), Mexican peso (MXN) and Peruvian sol (PEN) – than the prices of domestic products.

## 5.3. The global US dollar rally and the macroeconomic environment in Colombia

### 5.3.1. The global US dollar rally

An important challenge faced by analysts of ERPT is that both prices and exchange rates are endogenous. To solve this issue, several contributions focus on "clean exchange rate shocks" (Bonadio & Fischer & Sauré, 2019, p.507), i.e. changes in the nominal exchange rate that are driven by developments on financial markets, political decisions, or changes in investor sentiment, but are arguably not reflecting endogenous reactions to the evolution of domestic prices. Such an event could be observed in many countries around the globe (including Colombia) between mid-2014 and early 2015, when the US dollar appreciated against most currencies in the world. Figure 1a depicts the evolution of the dollar's nominal effective exchange rate, which increased by 13.48 percent between July 2014 and March 2015 after more than one year of stability. We label this period the *global US dollar rally*. Of course, the time series in Figure 1a is not informative about the appreciation vis-á-vis individual currencies, but it documents the global scale of the US dollar rally.

Importantly – and in contrast to the episodes analyzed, e.g., by Burstein & Eichenbaum & Rebelo (2005) – the US dollar appreciation did not reflect a crisis in any of the countries involved. Instead, it predominantly mirrored markets' re-assessment of the Fed's future monetary policy and of the country's growth prospects. Two US monetary policy-related factors were primarily held accountable for the global US dollar's strength: First, the Federal Open Market Committee (FOMC) reduced the pace of its asset purchases several times in 2014.[2] And second, expectations spread that the Fed would start raising interest rates in 2015 from historic lows. This (expected) monetary policy tightening in the US clashed with a still extremely loose monetary policy stance in many other economies in the world. In addition to this ongoing monetary policy divergence, the (relative) strength of the US economy and low commodity prices contributed to a strong US dollar. As the Financial Times reported in a 2014 end-of-year review: "Investors have been reversing the trend of the past few years to put money outside the US in search of higher yields and stronger returns in emerging markets as interest rate expectations have shifted and the US economy has powered ahead."[3] In a similar spirit, the IMF in its 2015 *Annual Report on Exchange Arrangements and Exchange Restrictions* (AREAER) relates the appreciation of the US dollar to "...shifts in markets' expectation of the Federal Reserve's interest rate liftoff" (p.2).

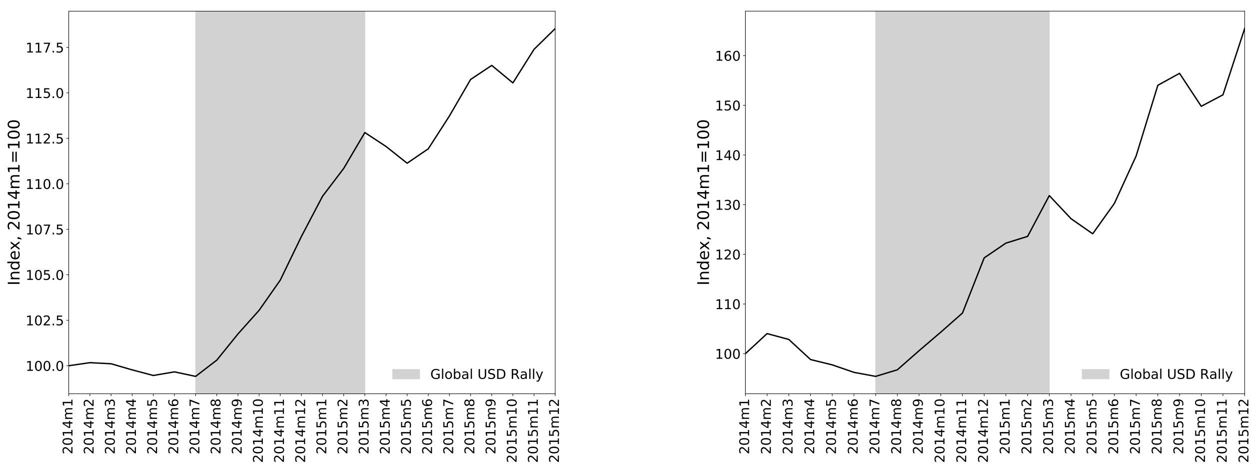
While the scanner data set we use covers a large number of countries, we initially focus on the evolution of prices in Colombia for the following reasons: First, as documented by Figure 1b, the appreciation of the US dollar against the Colombian peso was particularly sharp, amounting to 40 percent between July 2014

[2]In the statement on December 18, 2013, the FOMC announced "to modestly reduce the pace of its asset purchases". In each of the FOMC statements from January 2014 to September 2014, the FOMC announced "to make a further measured reduction in the pace of its asset purchases", and in the FOMC statement on October, 29, 2014, the FOMC announced "to conclude its asset purchase program this month". See `https://www.federalreserve.gov/monetarypolicy/fomchistorical2014.htm`.

[3]From the Financial Times. December 31, 2014: "Dollar surges in 2014 on rate rise hopes".

and March 2015, and occurred after a long period of USD/COP stability.[4] In fact, the rapid increase of the exchange rate satisfies the criteria of a "currency crash" established by Frankel & Rose (1996, p.3), who define a currency crash as a "nominal depreciation of the currency of at least 25 percent [in a year] that is also at least a 10 percent increase in the rate of depreciation." The currency crash in Colombia is, however, not being associated with the typical symptoms of a "currency crisis" (Kaminsky & Lizondo & Reinhart, 1998), i.e. large-scale stress in the financial system, wide-spread bankruptcies, or a deterioration in gross international reserves.[5]

Figure 1: US dollar exchange rates, 2014-2015




(a) USD NEER. Source: St. Louis Fed

(b) Nominal USD/COP exchange rate. Source: IMF

Second, the US dollar plays a dominant role as import invoicing currency in Colombia – i.e. import prices should have been affected particularly strongly by the US dollar rally. Table 1 reveals the high US dollar import share in Latin American countries provided by Boz et al. (2022). Surprisingly, Colombian imports are not documented in the data set, but we conjecture that the importance of the US dollar is comparable to the import share in the other Latin American countries. In addition, Gopinath et al. (2016) and Gopinath et al. (2020) document a high and instant pass-through of variations in the USD/COP exchange rate into prices charged by Colombian exporters and importers.

We thus argue that, from the Colombian perspective, the US dollar rally was exogenous, which solves one of the key problems when it comes to identifying the causal effect of exchange rate movements on prices. Moreover, the USD/COP exchange rate change was particularly sharp, and most of the US dollar appreciation took place within a relatively short period of time, which suggests using an event-study design to assess the

[4]Apparently, the US dollar kept appreciating against the Colombian peso after a short pause in spring 2015. However, our analysis will focus on the first nine months of the US dollar rally. This is because, as the time period considered grows larger, it becomes increasingly difficult to relate price movements (exclusively) to exchange rate fluctuations.

[5]According to the World Bank's WDI, the share of non-performing loans relative to Colombian banks' total loans increased from 2.77 percent in 2013 to 2.92 percent in 2014 and dropped back to 2.85 percent in 2015. According to Kaminsky & Lizondo & Reinhart (1998), a "currency crisis" usually leads to a large decline in international reserves. In Colombia, however, gross international reserves increased from 37,871 million US dollars in January 2013 to 46,099 million US dollars in July 2014 and then remained fairly stable with an end-of-2015 balance of 46,740 million US dollars.

Table 1: US dollar % import invoicing share in Latin American countries, 2012 to 2018, annual frequency. Source: Boz et al. (2022)

| Year | Argentina | Brazil | Chile | Costa Rica | Ecuador | Paraguay | Peru | Uruguay |
|---|---|---|---|---|---|---|---|---|
| 2012 | 87.13 | 86.31 | 88.12 | 98.64 | NA | NA | 93.27 | NA |
| 2013 | 87.84 | NA | 86.50 | 97.58 | NA | NA | 92.90 | NA |
| 2014 | 87.39 | NA | 87.23 | 97.52 | NA | 95.17 | 93.15 | NA |
| 2015 | 87.52 | NA | 86.06 | 96.60 | 94.78 | 94.95 | 93.88 | 75.50 |
| 2016 | 87.75 | NA | 83.18 | 97.57 | 93.46 | 94.62 | 92.86 | 70.40 |
| 2017 | 87.74 | 81.15 | 83.08 | 97.12 | 93.47 | 94.97 | 91.93 | 64.50 |
| 2018 | 88.13 | 83.36 | 83.11 | 97.12 | 93.72 | 94.99 | 91.60 | 67.70 |

extent and speed of exchange-rate pass-through. Finally, Colombian import prices should have been affected particularly strongly by the US dollar rally, as the US dollar plays a dominant role as invoicing currency for Colombian imports.

### 5.3.2. The Colombian macroeconomy before, during and after the global US dollar rally

The Colombian economy did not exhibit signs of macroeconomic volatility between July 2014 and March 2015. This is of crucial importance for the event-study analysis, as a simultaneous occurrence of currency depreciation and macroeconomic turmoil would hamper the use of an event-study framework.

Colombia entered 2014 with a very strong and robust economy. Colombia's real GDP growth averaged 4 percent and annual inflation averaged 2.7 percent (close to its target of 3 percent) in the five years prior to 2014. The IMF projected in its 2014 Staff Country Report on Colombia (p.1) that real GDP growth will "converge to potential (about 4,5 percent) in 2014, with inflation remaining within the 2-4 percent target range". Figure 2a plots year-to-year changes in real GDP and Figure 2b plots year-to-year changes in the consumer price index in 2014 and 2015. Indeed, real GDP was growing steadily in 2014 and the first three quarters of 2015, and experienced a drop in the growth rate in the final quarter of 2015. Inflation exhibited an upward trend in 2014 and 2015 and escaped the 2-4 percent target range at the beginning of 2015. However, none of these evolutions was disruptive.

Colombia's economy has important ties with the global economy. As a commodity exporter[6], Colombia's economy is sensitive to oil prices. As Colombia had a floating exchange rate regime, as classified and identified by the IMF throughout all years in the 2010s[7], external shocks, like monetary policy shifts in the United States, have a strong impact on the external value of the Colombian peso. Just when the US dollar started to gain strength in the third quarter of 2014, oil prices plummeted. Figure 2c shows the World Spot Crude Index in 2014 and 2015. The index dropped sharply by over 44 percent between July 2014 and March 2015.

Colombia's real economy absorbed the severe drop in oil prices and the global US dollar rally remarkably

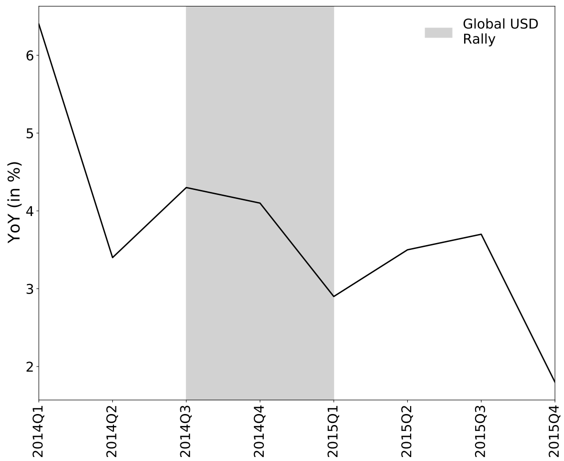
[6] Petroleum exports including derivatives accounted for more than 50 percent of total exports "free on board" in US dollars in 2013 and 2014, and to around 40 percent of total exports "free on board" in US dollars in 2015 according to oil export shares published by the *Departamento Administrativo Nacional de Estadística* (DANE).

[7] See AREAER summary feature tables on `www.elibrary-areaer.imf.org`.

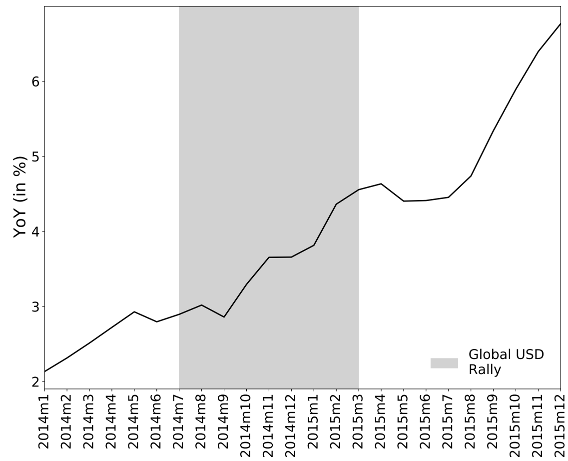
well. Figure 2d plots year-to-year changes in real consumption. Real consumption was central to solid real GDP growth in 2014 and the first three quarters of 2015. In addition, historically low unemployment rates were observed in 2014 and 2015 (see Figure 2e).

All in all, the exogenous and sharp Colombian peso depreciation vis-á-vis the US dollar, the high reliance of Colombian import prices on the US dollar and the strong and robust Colombian economy turns Colombia into our "flagship country" to analyze retail price movements during the global US dollar rally of July 2014 to March 2015 in an event-study framework.

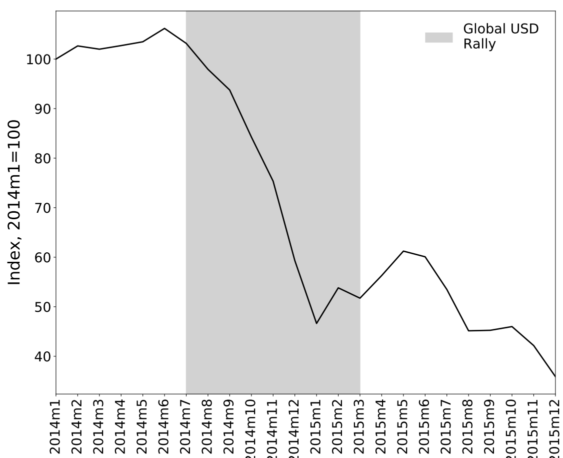
Figure 2: Macroeconomic indicators in Colombia, 2014-2015



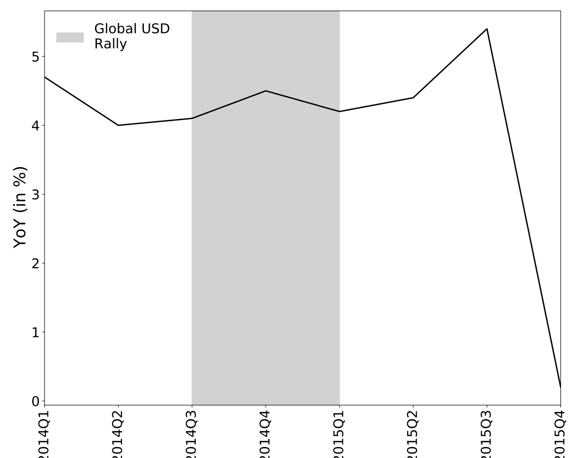

(a) Real GDP growth. Source: DANE



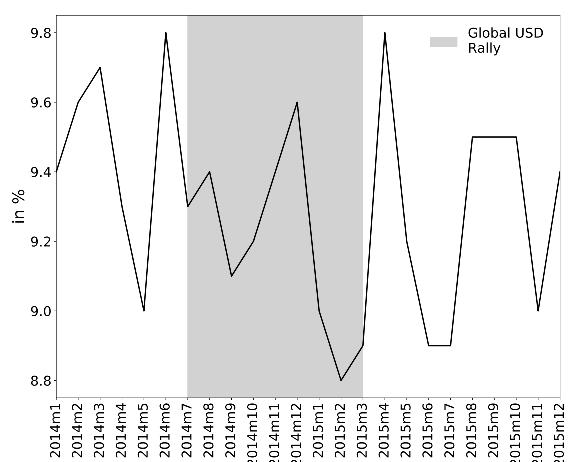

(b) CPI growth. Source: DANE




(c) World Spot Crude Oil Index. Source: IMF




(d) Real consumption growth. Source: DANE




(e) Seasonally adjusted unemployment rate. Source: DANE

## 5.4. The scanner data set

In our empirical examination, we make use of a large micro scanner data set, covering purchases of "fast-moving consumer goods" (FMCG) in Colombia in 2014 and 2015. FMCG are consumed frequently by households, transacted at relatively low prices and generally fall into the product categories food and beverages, as well as personal and household care.

The scanner data set is provided by Kantar, a multinational market research firm that collects market research data globally, and can be classified as a household scanner data set, as households report their purchases digitally using scanner technology.[8] The scanner data set provides detailed transaction information at high frequency, tracking a nationally representative panel of consumers. We briefly highlight the main features of the scanner data set, explain important data cleaning steps and present some summary statistics.

In our scanner data set, we obtain information on total value transacted and total quantity transacted by time (day of transaction) and place of purchase (retailer and retailer type) at the barcode level. In addition to expense and quantity information, we obtain detailed features of each transacted product (=barcode) in a separate product dictionary file, including a precise product description (with up to 5 product characteristics), weight and size information, as well as brand and category affiliation. In total, 161 product groups (= "subcategories") are covered, which are defined at a very granular level, usually below the 5-digit *Classification of Individual Consumption by Purpose* (COICOP). The scanner data set is also supplemented by a household dictionary file that shows socio-demographic information (household size, education, income, etc.) collected from households through survey questionnaires. A snapshot of the (merged) data set (=scanner data set + information from product dictionary file + information from household dictionary file) is shown in Table 2. A corresponding summary of the complete data set (after having dropped transactions with missing or negative total value or total quantity information and after having applied an outlier filter to the data[9]) is presented in Table 3.

One key advantage of our data set is that it allows us to distinguish between imported and domestic products. Following Bems & Giovanni (2016), we identify the domestic/foreign origin of each transacted product via barcode characteristics. In particular, the first three digits of the Global Trade Identification Number (GTIN) identify the country in which the label was applied for. The product identifiers/barcodes that do not coincide with a GTIN are usually assigned by the data provider as globally standardized barcode information is missing, with the bulk falling into staple food product categories such as bread, liquid milk

[8]Household scanner data "collected by individuals or households using scanner technology that is typically provided by a third-party company" is often contrasted with store scanner data "collected at the point of sale by the in-store scanners used at check-outs" (Dubois & Griffith & O'Connell, 2022, p.1). Although both forms of scanner data share a number of key features, household scanner data offer the following attractive features: i) they usually cover transactions in a multitude of stores or retail chains; ii) they usually track households through time, which allows analyzing a household's choice behavior and to relate it to a household's socio-demographic information. See Dubois & Griffith & O'Connell (2022) for more information on scanner data and its benefits for economic research.

[9]The rationale for an outlier filter is to exclude transactions with unusually high or low total value and total quantity information, as these transactions may be prone to coding errors or other mistakes in the data set (Eurostat, 2022). We choose the following thresholds for identifying outlier transactions on a barcode-retailer level: A total-value-over-total-quantity ratio that is higher (lower) than three times (a third of) the median, and total units purchased higher than 25 times the median.

Table 2: Snapshot of the data set

| Date | Hh ID* | Ret. ID* | Ret. Type | Product ID* | Expense in COP |
|---|---|---|---|---|---|
| 17.06.2014 | 554556 | 31 | Neighborhood Store | 7702518021005 | 1000 |
| 07.11.2014 | 777284 | 44 | Big Chain | 7702025186440 | 3827.5 |
| 13.02.2015 | 665920 | 28 | Convenience Store | 7509546056098 | 3150 |
| 22.04.2015 | 445456 | 93 | Other Chain | 7709990556087 | 1231 |
| | | | | | |
| **Units** | **Volume** | **Measure** | **Category** | **Subcategory** | |
| 1 | 1 | Pack | Toilet Paper | Toilet Paper - Regular | |
| 2 | 864 | Gram | Biscuit | Biscuit - Sweet | |
| 1 | 75 | Milliliter | Dental Product | Dental Product - Toothpaste | |
| 2 | 1100 | Gram | Industrialized Bread | Industrialized Bread - Regular | |

**Note:** This snapshot ignores information on socio-demographic features of the households and some product features provided in the product dictionary file. *The household, retailer and product identifiers are randomized, i.e. they do not correspond to the true data to comply with data nondisclosure agreements.

Table 3: Summary of the data set

| | Complete | Reduced |
|---|---|---|
| Nr. of Transactions | 6,465,122 | 4,971,440 |
| Nr. of Households | 5,394 | 5,344 |
| Nr. of Retailers | 114 | 113 |
| Nr. of Retailer Types | 13 | 13 |
| Nr. of Products | 67,515 | 52,877 |
| Nr. of Categories | 65 | 65 |
| Nr. of Subcategories | 161 | 160 |
| Sum of Expense in COP | 20,023,691,299 | 14,931,666,601 |

and rice, primarily transacted in the retailer types neighborhood stores and bakeries.[10] A summary of the reduced data set – next to the summary of the complete data set – is presented in Table 3. Since the products we consider can, in theory, be manufactured anywhere in the world, and not necessarily in the country where the label was applied for, we check whether the GTIN-based domestic/foreign labeling identification is a valid proxy for the domestic/foreign origin (=manufacturing location). We focus on web-scraped data from `www.world.openfoodfacts.org` (which provides GTIN and country of manufacturing information on thousands of products) and find that the method of identifying the domestic/foreign origin using the first 3 digits of the GTIN has 96 percent accuracy in the case of Colombia, i.e. in 96 percent of all the web-scraped GTINs that have a country of origin attached and match with GTINs in our data set, the web-scraped information on domestic/foreign origin (=manufacturing location) coincides with the GTIN-based domestic/foreign labeling identification.

In the analysis section, we crucially rely on price indices. Several price index formulas can be applied in order to obtain (elementary) price indices.[11] Any formula takes prices and quantities as inputs. In scanner data with information on total value transacted and total quantity transacted, prices are unit values, i.e. total

[10] We dropped all transacted products for which we could not identify their – domestic or foreign – origin.

[11] Elementary price indices are price indices at the lowest level of aggregation. Thus, the elementary aggregate is defined as the lowest level at which reliable expenditure weighting information is available (see the Intersecretariat (IMF, ILO, etc.) Working Group Consumer Price Index Manual: Concepts and Methods, 2020, p.177).

value transacted over total quantity transacted, and the elementary aggregate is the *homogeneous product* level. The specification of a homogeneous product, i.e. the unit for which unit values and quantities are observed over time, is central to any price index formula, as mis-specifications may lead to unit value bias (Diewert & Lippe, 2010). When specifying homogeneous products, we group together transacted products with identical features. As shown by Chessa (2016a), grouping is a valid strategy in order to capture possible price increases after a "relaunch", which is defined as a product of the same quality that is transacted with a new barcode.[12] Two such relaunches in the data set are shown in Table 4.

Table 4: Relaunch examples

| **Product ID*** | **Origin** | **Volume** | **Measure** | **Category** | **Subcategory** |
|---|---|---|---|---|---|
| 7702047005330 | Domestic | 400 | Grams | Tomato Sauce | Tomato Sauce - Regular |
| 7702047138519 | Domestic | 400 | Grams | Tomato Sauce | Tomato Sauce - Regular |
| 7702001049998 | Domestic | 300 | Milliliters | Industrialized Juice | Industrialized Juice - Without Gas |
| 7702001550178 | Domestic | 300 | Milliliters | Industrialized Juice | Industrialized Juice - Without Gas |

| **Characteristic 1** | **Characteristic 2** | **Characteristic 3** | **Characteristic 4** | **Brand ID*** | **Manufacturer ID*** |
|---|---|---|---|---|---|
| Mashed | Pure | Valve Pack | NA | 213 | 18 |
| Mashed | Pure | Valve Pack | NA | 213 | 18 |
| Juice Drink | Light | Maracuja | Paper Carton | 754 | 97 |
| Juice Drink | Light | Maracuja | Paper Carton | 754 | 97 |

**Note:** The transacted products in the first two rows (and the transacted products in the last two rows) have identical (i) total volumes; (ii) (sub)category affiliation; (iii) manufacturer affiliation; (iv) brand affiliation; (v) domestic/foreign origin; and (vi) characteristics (identified by up to the 4th criteria), but have a different barcode. For the purpose of this paper, such transacted products are treated as homogeneous. *The product, brand and manufacturer identifiers are randomized, i.e. they do not correspond to the true data to comply with data nondisclosure agreements.

The difference between the number of transacted products (52,877) and the number of homogeneous products (47,092) is -10.94 percent. Thus, a homogeneous product may refer to a single transacted product or to a group of transacted products that share exactly the same features. On average, each homogeneous product comprises 1.12 transacted products.

On the place-of-purchase dimension, we combine retailers of the same type. The different retailer types, including information on number of transactions and total value transacted, are shown in Table 5. With this type of assortment, we keep the data highly disaggregated and capture quality differences between retailer types, while avoiding to blow up the product universe, i.e. the number of individual homogeneous products that may ultimately enter the price index compilation.

Table 6 provides information on the transaction of homogeneous products across different types of retailers. The table shows that the majority of these products (16,667) are transacted by a single retailer type, while

[12] Nakamura & Steinsson (2012) illustrate the importance of price adjustments that occur at the time of product replacements (observable in micro datasets) for exchange-rate pass-through estimates and for the construction of price indices. They argue that such price adjustments are "lost in transit" in a conventional price index, in which price changes of identical (transacted) products enter, and product replacements are only linked into the index. They propose a model of such a "product replacement bias" and conclude that "our adjustment is designed to address a situation where characteristics data are unavailable, and therefore it is not possible to calculate the quality-adjusted prices using hedonic methods. Ideally, future research using more detailed data will allow for more direct estimates of product replacement bias based on comparisons of the quality-adjusted prices of entering and exiting items." (p.3313). The richness of our scanner data set would allow us to provide direct estimates of a potential product replacement bias, which is, however, not a goal of this paper. More importantly, our results are not prone to this "product replacement bias" as we capture possible price increases after relaunches/product replacements by grouping together transacted products with identical features.

Table 5: Expense by retailer type

| Retailer Type | Expense in COP | % Expense (Domestic) | % Expense (Imported) |
|---|---|---|---|
| **Neighborhood Stores** | 3,366,971,608 | 22.55 | 1.23 |
| **Convenience Stores** | 3,106,573,456 | 20.80 | 2.77 |
| **Big Chains** | 2,601,083,600 | 17.42 | 3.24 |
| **Other Chains** | 2,226,228,180 | 14.91 | 3.14 |
| **Other Channels** | 412,344,798 | 2.76 | 0.87 |
| **Bakeries** | 322,331,425 | 2.16 | 0.13 |
| **Hyperstores** | 295,734,035 | 1.49 | 0.46 |
| **Specialty Stores** | 221,928,073 | 0.91 | 0.56 |
| **Drugstores** | 130,954,445 | 0.53 | 0.33 |
| **Catalogs** | 78,844,009 | 0.52 | 2.43 |
| **Marketplaces** | 70,469,571 | 0.37 | 0.09 |
| **Warehouses / Wholesalers** | 40,748,923 | 0.21 | 0.05 |
| **Virtual Shops** | 821,662 | 0.01 | 0.01 |

**Note:** The retailer-to-retailer-type affiliation is provided by Kantar.

the remaining products are transacted by at least two different types of retailers. Specifically, 8,091 products are transacted by two types of retailers, 5,683 by three types, and so on. The table also shows that the number of products transacted decreases as the number of retailer types increases, with only one product being transacted across 13 different types of retailers.

Table 6: Products by count of retailer types

| Count of Retailer Types | Count of Homogeneous Products |
|---|---|
| 1 | 16,667 |
| 2 | 8,091 |
| 3 | 5,683 |
| 4 | 4,592 |
| 5 | 3,602 |
| 6 | 2,717 |
| 7 | 1,828 |
| 8 | 1,068 |
| 9 | 539 |
| 10 | 240 |
| 11 | 64 |
| 12 | 7 |
| 13 | 1 |

Figure 3 plots the differences in median unit values of homogeneous products relative to neighborhood stores (the retailer type with the highest expense). In total, 15,766 homogeneous products are sold in neighborhood stores and at least one other retailer type. As Figure 3 shows, median unit values of the same homogeneous product differ across retailer types. Thus, aggregation across retailer types is not acceptable as it may lead to unit value bias. The difference between the number of unique homogeneous product-retailer type combinations (131,970) and the number of homogeneous products (47,092) is -64.32 percent. This implies that one and the same homogeneous product is on average transacted in 2.8 different retailer types.

In order to observe a single unit value for each homogeneous product at the retailer type level, we sum total value transacted and total quantity transacted by retailer type and month, and then divide total value transacted by total quantity transacted. From now on, we define a homogeneous product at the retailer type level that may ultimately enter the price index computation simply as a ”product”. The aggregated data set (on an annual level) is summarized in Table 7.

Table 7: Summary of the aggregated data set

| | **Year** | **Sales Value in COP** | **% Sales Value Growth** | **Nr. of Homogeneous Products** |
|---|---|---|---|---|
| **All Products** | 2014 | 7,226,600,036 | NA | 94,501 |
| **All Products** | 2015 | 7,705,066,565 | 6.62 | 96,974 |
| **Domestic** | 2014 | 4,552,359,647 | NA | 72,082 |
| **Domestic** | 2015 | 4,821,714,372 | 5.92 | 74,723 |
| **Imported** | 2014 | 2,674,240,389 | NA | 22,419 |
| **Imported** | 2015 | 2,883,352,194 | 7.82 | 22,251 |

A distinct feature of scanner data sets is that they are typically dynamic in the sense that some products are not continuously purchased throughout the years, new products start being transacted (usually because they enter the market) and obsolete products stop being transacted (usually because they are removed from the assortments). Figure 4 shows that a minority of all products are transacted in each month between January 2014 and December 2015. More specifically, these are 4,802 products that capture 48.37 percent of total value transacted. Figure 5 shows that the product universe in our scanner data set is steadily changing over time. The percentage of products that are transacted in two adjacent months (”flow”) lies above both the percentage of products that are not transacted in the next month (”outflow”) and the percentage of products that had not been transacted in the previous month (”inflow”)[13], but inflows and outflows are substantial in each month.[14] This implies that price indices based on a *static product universe*, i.e. based on ”continuously transacted products” throughout all months in 2014 and 2015, may differ from price indices based on a *dynamic product universe*, which allows for a changing basket, and thus product entry and exit.

[13]As Chessa & Verburg & Willenborg (2017) highlight, ”inflow” does not only contain new products, but also products that are temporarily unavailable, and ”outflow” does not only capture products that disappear forever.

[14]Adjusted for expenditure, flows play a more dominant role.

Figure 3: Median unit value dispersion

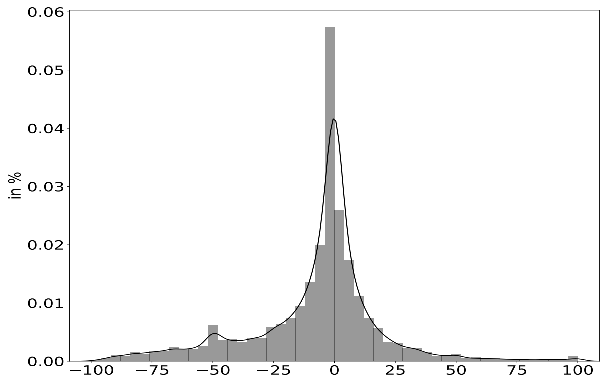



Figure 4: Transacted products by number of months

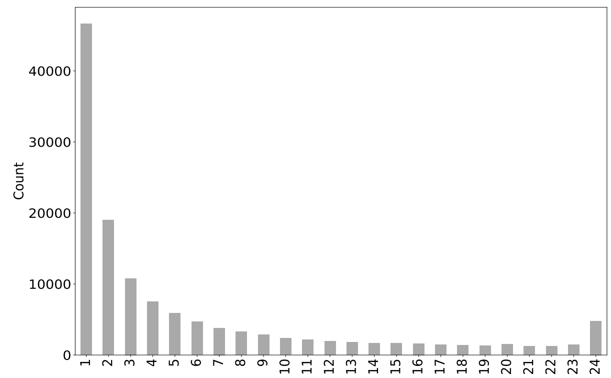
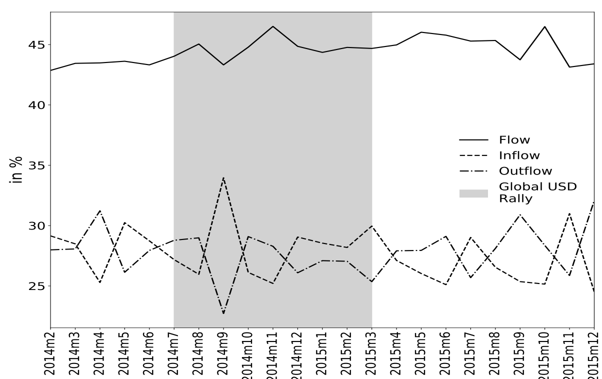



Figure 5: Flow, inflow and outflow of products




## 5.5. Colombian-specific analysis

### 5.5.1. Reconstructing the official FnB price index

Our first step is to determine whether our dataset can be used to track official price indices in Colombia. To do so, we must follow procedures similar to those used by the *Departamento Administrativo Nacional de Estadística* (DANE), which is responsible for compiling and publishing official economic statistics in Colombia. According to DANE's methodological datasheets and technical bulletins, unweighted geometric averages of price relatives are computed below the COICOP subclass level. These index numbers are then aggregated using arithmetic averages and weights from the National Household Budget Survey (NHBS), which was conducted in 2016-2017 and before that in 2006-2007, to create higher-level indices such as the COICOP division level for Food and non-alcoholic Beverages (FnB).

DANE's monitoring basket of goods and services, which is representative of household expenditures, consists of 443 items or representative products at the COICOP 7-digit level. Each month, DANE records prices for one or multiple varieties of each representative product. Although the selected varieties are not published, DANE states that they choose the most commonly sold varieties, which are expected to remain on the market for some time. If a variety is no longer available, it is replaced by a similar substitute.

To replicate DANE's procedure with our dataset, we should thus select a sample of frequently transacted products, weight products according to their economic importance, keep consumption baskets fixed, and compute monthly price variations. By following these procedures, we can determine whether our dataset can be used to track official price indices in Colombia.

We decided to compute the Laspeyres index on the "static product universe", meaning that we did not consider changes in the availability of products over time by relying on the products that were purchased at least once every month in 2014 and 2015. This approach is similar to the one used by Braun & Lein (2021), who utilized a "super common varieties sample" to replicate the official price index computed by the Swiss Federal Statistical Office with scanner data on prices and expenditures in the CPI subgroups of food, beverages, and tobacco. The "super common varieties sample" consists only of products that are purchased at least once every quarter. By focusing on continuously transacted products, we aim to approximate the frequently transacted goods sample and fixed consumption basket used by DANE in its price index calculation. Moreover, we limit our analysis to products that could be classified under the FnB division, which has the highest total value transacted in our data set (58 percent), and for which we could obtain official price index numbers. This division accounted for 20.14 percent of the total consumption basket derived from the NHBS conducted in 2006-2007 and 17.93 percent of the total consumption basket derived from the NHBS conducted in 2016-2017. To compute the Laspeyres (1871) index numbers between two consecutive periods, we used the following formula:

$$P_{s,t} = \frac{\sum_{i \in \Omega_s} p_{it} q_{it-1}}{\sum_{i \in \Omega_s} p_{it-1} q_{it-1}} \tag{2}$$

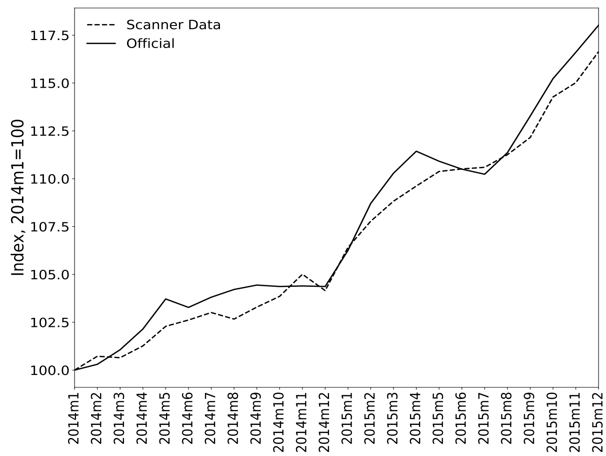
where $\Omega_s$ refers to the set of continuously transacted products that belong to the FnB division. Finally, we chained the Laspeyres period-on-period index numbers to obtain the cumulative Laspeyres index.

Figure 6 displays the Laspeyres FnB index based on our reduced scanner data set and the official consumer price FnB index published by DANE. Three key observations are worth noting: First, the two lines move in parallel, indicating that the information incorporated in both indices is quite similar. Second, there were two waves of price hikes, one in the first quarter of 2015 and the other at the end of 2015, beginning in September. Finally, the rise in FnB prices of roughly five percentage points during the USD rally (July 2014 to March 2015) is rather low compared to the almost 40 percent increase in the US dollar over the same period (see Figure 1b).

### 5.5.2. Relative price movements (imported over domestic products)

Of course, the moderate pass-through of the US dollar appreciation into the FnB retail price index as such is not puzzling. It is well known that the "retail wedge" isolates prices from exchange rate fluctuations – at least in the short run (see Burstein & Gopinath, 2014). This is because the distribution services that are necessary to take imported products from the border to the store shelf entail a large non-traded component, which is not

Figure 6: Official vs. Data Set based FnB Price Index, 2014-2015




**Note:** The data set based FnB price index is a Laspeyres index based on the static product universe. Source: DANE

directly affected by exchange rate fluctuations. The specific role of distribution services for ERPT depends on whether they enter the production of retail goods in a multiplicative or in an additive way. In the first case – as, e.g., in Breinlich et al. (2021) – prices at the wholesale level are independent of the retail industry. In the second case – as in Corsetti & Dedola (2005) or Harms & Hoffmann & Ortseifer (2015) – the existence of distribution costs affects the markup charged by producers. Moreover, the "retail wedge" hinges on the market structure in the retail industry, with the assumption of perfect competition being a frequent, but not obvious choice. Finally, exchange rate fluctuations may affect the costs at which distribution services are produced (Breinlich et al., 2021). Despite the dampening effect of the "retail wedge", we conjecture that – at least in the short run – a depreciation of the domestic currency raises the prices of imported products by more than the prices of their domestically produced substitutes. The plausibility of this conjecture is supported by Burstein & Gopinath (2014) who observe that prices of domestically produced goods are insensitive to nominal exchange rates (p.415). Moreover, in their analysis of "Brexit depreciation", Breinlich et al. (2021) do not find evidence that, in the time frame considered, domestic firms raised the prices of products that are close substitutes to imported products. An obvious explanation for these observations is that price-stickiness impedes a swift reaction of domestic product prices. To verify our expectation that the appreciation of the US dollar increased the prices of imported products by more than the prices of close domestic substitutes, we consider the evolution of subcategory-specific *price ratios* that divide a price index for imported products by a price index for domestic products of the same subcategory. More specifically, we compute:

$$\rho_{gt}^{T} = \frac{P_{gt}^{M,T}}{P_{gt}^{D,T}} \tag{3}$$

where $P_{gt}^{j,T}$ (with $j = M, D$) gives a period-on-period *Tornqvist price index number* (Tornqvist, 1936) for imported (M) and domestic (D) products assigned to subcategory $g$, i.e.:

$$P_{gt}^{j,T} = \prod_{i \in \Omega_g^j} \left( \frac{p_{it}}{p_{it-1}} \right)^{(s_{it-1}+s_{it})/2} \tag{4}$$

where $\Omega_g^j$ is the set of imported/domestic products assigned to subcategory $g$, $p_{it}$ is the price of product $i$ at time $t$, $p_{it-1}$ is the price of product $i$ at the previous period, and $s_{it}$ is the share of period $t$ expenditure on product $i$ defined as:

$$s_{it}^j = \frac{p_{it}q_{it}}{\sum_{i \in \Omega_g^j} p_{it}q_{it}} \tag{5}$$

The denominator of the expression is the total expenditure on all imported/domestic products in period $t$. The period-on-period index numbers are then chained, i.e. the price index is calculated as the cumulative product of the period-on-period index numbers.

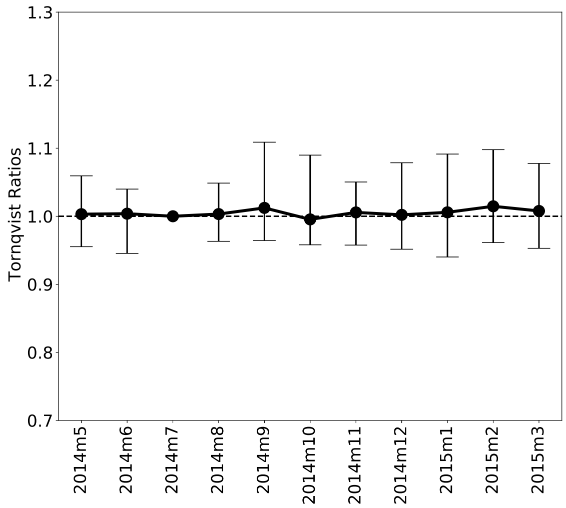
Figure 7a illustrates the distribution of $\rho_{gt}^T$ across different product subcategories $g$ for the *static product universe*, i.e. we restrict the sets $\Omega_g^M$ and $\Omega_g^D$ to those products that are purchased at least once every month in 2014 and 2015. Figure 7b illustrates the distribution of $\rho_{gt}^T$ for the *dynamic product universe*, i.e. we resample the sets for each pair of adjacent periods being compared and thus let the sets $\Omega_g^M$ and $\Omega_g^D$ vary over time. Interestingly, Figure 7a does not reveal the increase in the (empirical) distribution of $\rho_{gt}^T$ that we would have expected. In fact, the price ratio remains surprisingly stable, with the median moving sideways and the 10th/90th percentiles of the data remaining below/above the 1.0-line. The fact that relative prices of imported products over their domestic substitutes remain constant comes as a surprise, and contradicts the wide-spread notion that exchange rate movements generate relative price movements. Figure 7b documents that the surprising stability of relative prices does not disappear, even if we allow for changes in the availability of products over time.

### 5.5.3. Separate price indices (imported and domestic products)

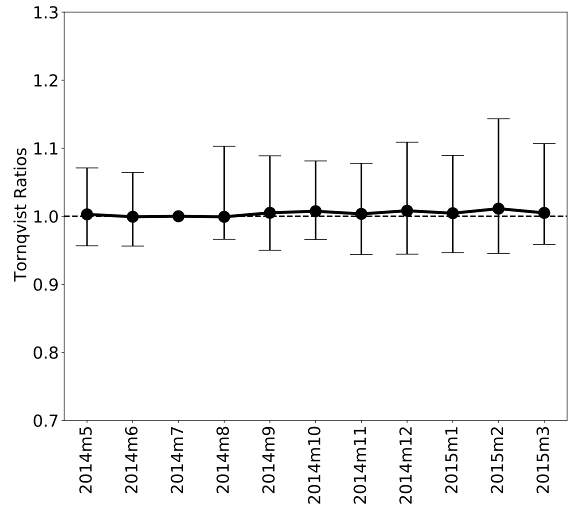
The surprising stability of relative prices documented in the preceding subsection allows for different interpretations: Possibly, neither imported nor domestic product prices change despite the considerable depreciation of the Colombian peso. Or both change over time, but move in parallel. To explore which of the two interpretations is supported by the data, we compute separate price indices for imported and domestic products. We restrict the analysis to those products and subcategories that enter the price ratios in Figure 7.

To calculate an origin-specific price index, we first compute period-on-period Tornqvist price index numbers at the subcategory level by assigning weights to all products within a subcategory. Then, we aggregate the individual index numbers using subcategory-origin specific weights and ultimately chain the aggregated index

Figure 7: Distribution of price index ratios around the US dollar rally




(a) Tornqvist, static product universe




(b) Tornqvist, dynamic product universe

**Note:** This figure illustrates the distribution of $\rho_{gt}^{T}$ as defined by equations (3) to (5) across different product subcategories $g$. The medians are denoted by dots. The whiskers define the 90th and 10th percentile of the data, respectively. The left column is based on the static product universe and the right column is based on the dynamic product universe. We restrict the analysis to 51 subcategories (static product universe) and 60 subcategories (dynamic product universe) for which we observe at least 5 domestic and imported products.

numbers to observe the price index. More specifically, we compute:

$$P_t^{j,T} = \sum_g \prod_{i \in \Omega_g^j} \left( \frac{p_{it}}{p_{it-1}} \right)^{(s_{it-1}+s_{it})/2} W_{gt-1}^j \tag{6}$$

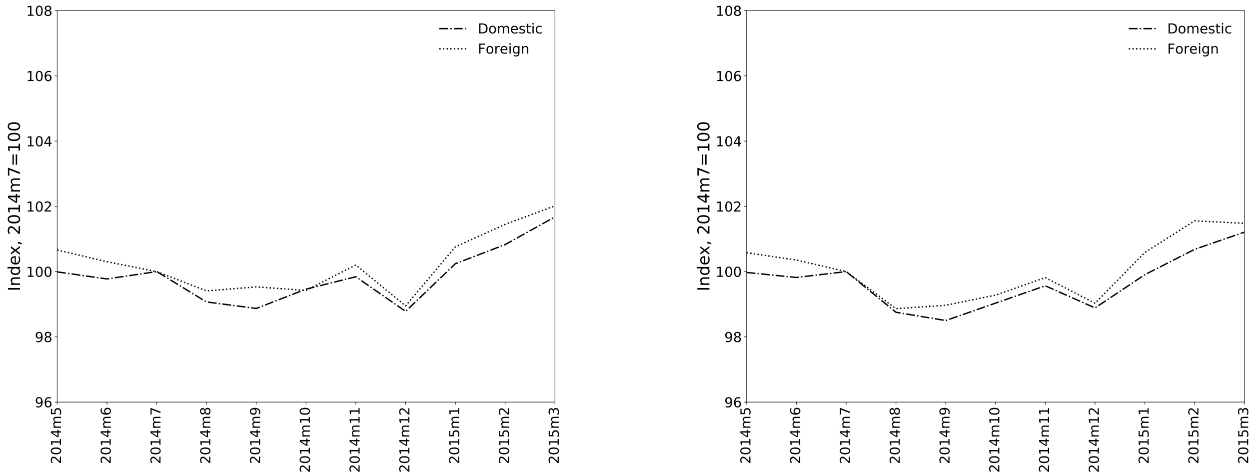
with

$$W_{gt-1}^j = \frac{\sum_{i \in \Omega_g^j} p_{it-1} q_{it-1}}{\sum_{i \in \Omega^j} p_{it-1} q_{it-1}} \tag{7}$$

Figure 8 illustrates the origin-specific price indices resulting from the static product universe and the dynamic product universe. It demonstrates the pick-up in inflation in the first quarter of 2015 that was already present in Figure 6.[15] Prices increased by approximately 3 percent in the first quarter of 2015, which amounts to an annualized inflation rate of approximately 12 percent. Interestingly, however, the upward movement appears in both the domestic and foreign price index. We thus conclude that both imported and domestic product prices change over time, but move in parallel.

[15]The inflation rates shown in Figure 6 and Figure 8a differ due to two factors. First, the product universe used to calculate each index differs: Figure 6 only includes FnB products, whereas Figure 8a includes FnB, personal care, and household products. Secondly, the formula used to calculate each index differs: The Laspeyres index used to compute the inflation rate in Figure 6 relies on base period expenditure shares, which may not accurately reflect changes in consumer behavior and preferences over time. On the other hand, the Tornqvist index used to calculate the inflation rate in Figure 8a updates both the quantities of goods consumed and the expenditure shares each period, which can better capture changes in consumer behavior and preferences over time. Overall, the Tornqvist index in Figure 8a is rated as the more accurate measure of inflation, while the Laspeyres index in Figure 6 was used to replicate the official FnB price index, which follows a methodology closer to the Laspeyres index.

Figure 8: Price indices by product origin around the US dollar rally




(a) Tornqvist, static product universe

(b) Tornqvist, dynamic product universe

**Note:** This figure presents Tornqvist price indices for imported and domestic products separately, which are calculated based on equations (6) to (7), using the static product universe (left column) and the dynamic product universe (right column). The analysis focuses on 51 subcategories (static product universe) and 60 subcategories (dynamic product universe) with at least 5 observed domestic and imported products, which corresponds to the product universe used in the price index ratio plots presented in Figure 7.

### 5.5.4. Spending patterns

The fact that we observe constant ratios of imported over domestic product prices within a subcategory suggests that there was no significant impact on consumers' (relative) spending behavior. We therefore conjecture that consumers did not systematically switch from imported products to domestic products, or vice versa, in the wake of the US dollar rally.

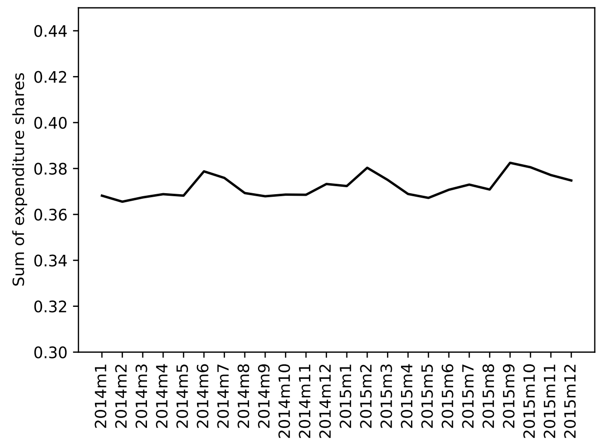
In order to explore whether domestic products gained market share during the US dollar rally, we compute the aggregate import expenditure share from product-level data for each month in 2014 and 2015 via:

$$s_t^M = \sum_g \sum_{i \in \Omega_{gt}^M} s_{igt} \tag{8}$$

Here $s_{igt}$ refers to the expenditure share on product $i$ in subcategory $g$ in period $t$, $\Omega_{gt}^M$ is a subset of imported products in subcategory $g$ in period $t$, and $\sum_g \sum_i s_{igt} = 1$, i.e. expenditure shares sum up to one over all products and subcategories in period t. Figure 9 shows that the aggregate import expenditure share was constant. In other words, consumers did not switch their spending from domestic products to imported products, or vice versa, during the period of analysis.

Although we observe that the aggregate import expenditure share remained constant, which indicates that the proportion of overall spending on imported products did not change over time, we cannot conclude that consumers did not switch from imported to domestic products *within* a narrowly defined subcategory. To understand whether such switching occurred, we need to examine whether import expenditure shares and

Figure 9: Aggregate import expenditure share, 2014-2015




**Note:** This figure plots the aggregate import expenditure share as defined by equation (8) based on all products in the (reduced) data set.

relative quantities of imported and domestic products within a subcategory also remained constant. To start with the former, we define the share of imports within a subcategory as:

$$\phi_{gt}^{M} = \frac{s_{gt}^{M}}{s_{gt}} \tag{9}$$

Figure 10 plots the distribution of import expenditure share year-on-year growth rates for the first four months in 2015. All four subfigures show a distribution centered around zero with an import expenditure share growth rate of the median subcategory of zero or at most 1 percent.

Next, we compute quantity indices on a subcategory level to explore potential quantity effects. If these relative quantities changed, then consumers could have shifted their preferences from domestic to imported products, or vice versa, even if the aggregate import expenditure share remained constant. Formally, we compute:

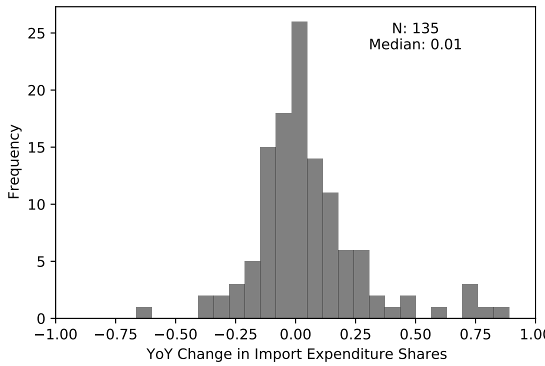
$$\sigma_{gt}^{T} = \frac{Q_{gt}^{M,T}}{Q_{gt}^{D,T}} \tag{10}$$

where $Q_{gt}^{j,T}$ (with $j = M, D$) gives a period-on-period *Tornqvist quantity index* number for imported (M) and domestic (D) products assigned to subcategory $g$, i.e.:

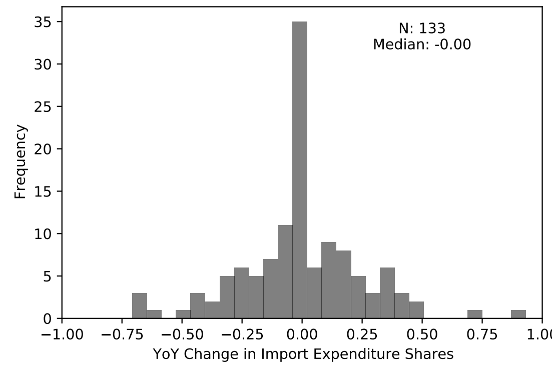
$$Q_{gt}^{j,T} = \prod_{i \in \Omega_g^j} \left( \frac{q_{it}}{q_{it-1}} \right)^{(s_{it-1}+s_{it})/2} \tag{11}$$

where $\Omega_g^j$ is the set of imported/domestic products assigned to subcategory $g$, $q_{it}$ is the quantity of product $i$ at time $t$, $q_{it-1}$ is the quantity of product $i$ at the previous period, and $s_{it}$ is the share of period $t$ expenditure

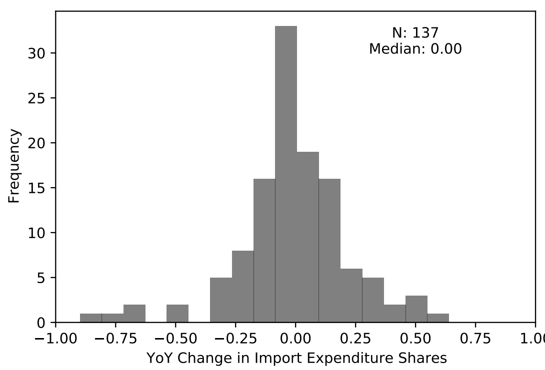
Figure 10: Distribution of import expenditure share growth rates



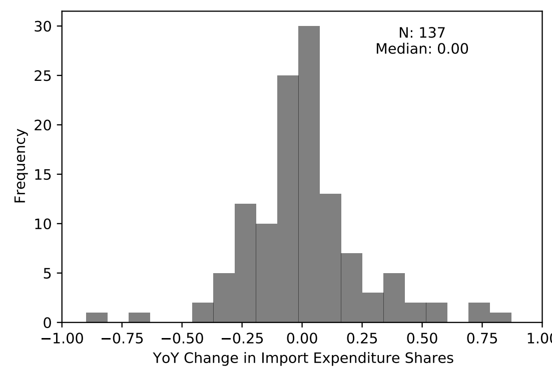

(a) YoY, 2015m1 vs. 2014m1




(b) YoY, 2015m2 vs. 2014m2




(c) YoY, 2015m3 vs. 2014m3




(d) YoY, 2015m4 vs. 2014m4

**Note:** This figure shows the distribution of import expenditure share year-on-year growth rates for the first four months in 2015 as defined by equation (9). Included are all subcategories with non-zero expenditures in the two relevant time periods.

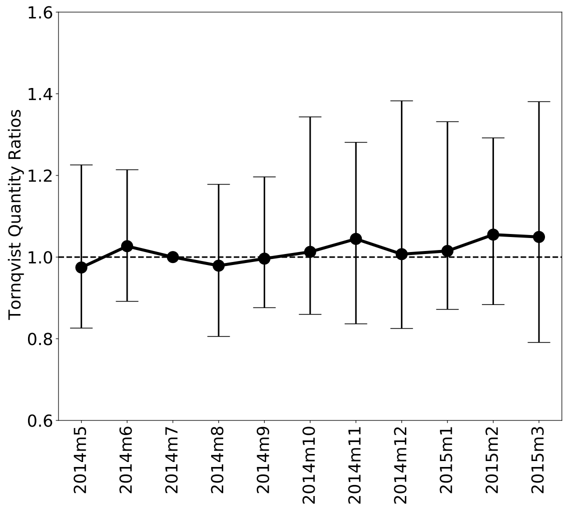
on product $i$ defined (as before) as:

$$s_{it}^{j} = \frac{p_{it} q_{it}}{\sum_{i \in \Omega_g^j} p_{it} q_{it}} \tag{12}$$

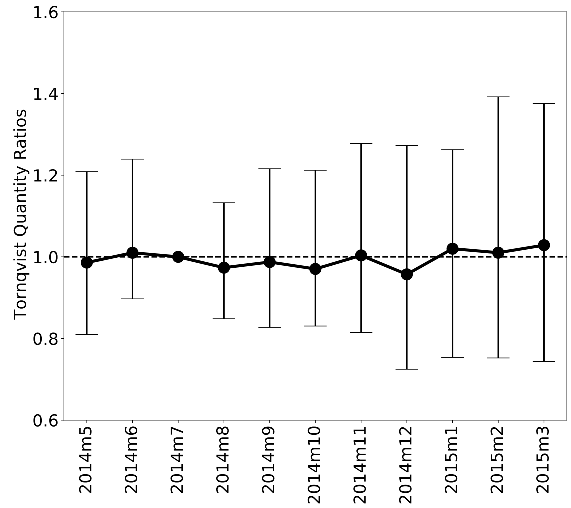
with the resulting quantity indices being computed as chained indices based on the underlying index numbers.

Figure 11 plots the distribution of $\sigma_{gt}^{T}$ around the time of the global US dollar rally. The sideways moving median and 10th/90th percentile of the data supports our conjecture that stable relative prices do *not* result in large-scale expenditure switching.

Figure 11: Distribution of quantity index ratios around the US dollar rally




(a) Tornqvist, static product universe




(b) Tornqvist, dynamic product universe

**Note:** This figure illustrates the distribution of $\sigma^T_{gt}$ as defined by equations (10) to (12) across different product subcategories $g$. The medians are denoted by dots. The whiskers define the 90th and 10th percentile of the data, respectively. The left column is based on the static product universe and the right column is based on the dynamic product universe. We restrict the analysis to 51 subcategories (static product universe) and 60 subcategories (dynamic product universe) for which we observe at least 5 domestic and imported products, i.e. the product universe matches with the one used for the price index ratio plots and origin-specific price indices.

## 5.6. Extending the focus beyond Colombia

Our findings for Colombia challenge the widely-held view that exchange rate fluctuations have a significant impact on relative prices faced by consumers and correspondingly on expenditure switching from imported to domestically produced products. Specifically, we observe that the retail sector seems to play a complex role in transmitting exchange rate fluctuations to off-the-shelf prices.

In order to assess the robustness and generalizability of our Colombian-specific findings, we aim to extend our analysis to other Latin American countries. By examining whether our results hold true in other countries with different economic characteristics, we can better understand the mechanisms underlying the transmission of exchange rate changes to relative retail prices in the region as a whole.

In what follows, we will construct Figures 7 and 11 for Brazil, Chile, Mexico and Peru conducting exactly the same data manipulation steps as described in Section 5.4.. In particular, we identify the domestic/foreign origin of each transacted product via barcode characteristics and group together transacted products with identical features in order to capture potential price increases after a relaunch. The number of products by domestic/foreign origin for each country is summarized in Table 8.

Table 1 shows that US dollar import invoicing shares for Brazil, Chile and Peru. With more than 85 percent import invoicing share in 2014 and 2015, the US dollar plays a dominant role in these countries and thus import prices should have been affected strongly by the US dollar rally. For Mexico, we conjecture that the US dollar import invoicing share is similar to what we observe for the other Latin American countries.

Table 8: Product count by origin

| | Brazil | | | Chile | |
|---|---|---|---|---|---|
| | Year | Nr. of Homogeneous Products | | Year | Nr. of Homogeneous Products |
| **All Products** | 2014 | 126,942 | **All Products** | 2014 | 49,092 |
| **All Products** | 2015 | 149,187 | **All Products** | 2015 | 48,458 |
| **Domestic** | 2014 | 118,762 | **Domestic** | 2014 | 32,988 |
| **Domestic** | 2015 | 139,132 | **Domestic** | 2015 | 32,762 |
| **Imported** | 2014 | 8,180 | **Imported** | 2014 | 16,104 |
| **Imported** | 2015 | 10,055 | **Imported** | 2015 | 15,696 |
| | **Mexico** | | | **Peru** | |
| | Year | Nr. of Homogeneous Products | | Year | Nr. of Homogeneous Products |
| **All Products** | 2014 | 75,699 | **All Products** | 2014 | 46,793 |
| **All Products** | 2015 | 86,184 | **All Products** | 2015 | 43,408 |
| **Domestic** | 2014 | 53,951 | **Domestic** | 2014 | 26,167 |
| **Domestic** | 2015 | 60,865 | **Domestic** | 2015 | 24,222 |
| **Imported** | 2014 | 21,748 | **Imported** | 2014 | 20,626 |
| **Imported** | 2015 | 25,319 | **Imported** | 2015 | 19,186 |

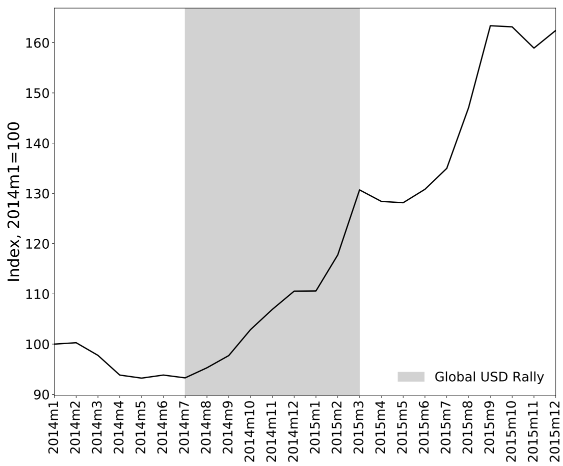
Figure 12a shows that the nominal appreciation of the US dollar against the Brazilian real (BRL) was as sizable as the US dollar appreciation against the Colombian peso, amounting to more than 40 percent between July 2014 and March 2015. Although the US dollar appreciated to a lesser extent against the Chilean peso (CLP), Mexican peso (MXN) and Peruvian sol (PEN) (see Figure 12b to 12d), it remained consistently strong, strengthening by at least 10 percent in all cases.

While event studies typically require a stable economic environment to identify the causal impact of an event on economic outcomes, a multi-country analysis can still provide valuable insights even in the presence of heterogeneity across countries. By examining the relationship between exchange rate fluctuations and consumer prices across a diverse set of countries with different economic conditions, we can identify patterns and trends that are robust to idiosyncratic shocks and policy differences. Moreover, the heterogeneity of economic conditions across countries can itself be a source of valuable information. By comparing the responses of different countries to a common shock, we can better understand the factors that contribute to variation in exchange rate pass-through and the factors that may moderate or amplify the impact of exchange rate fluctuations on (relative) prices – provided that there is any variation.

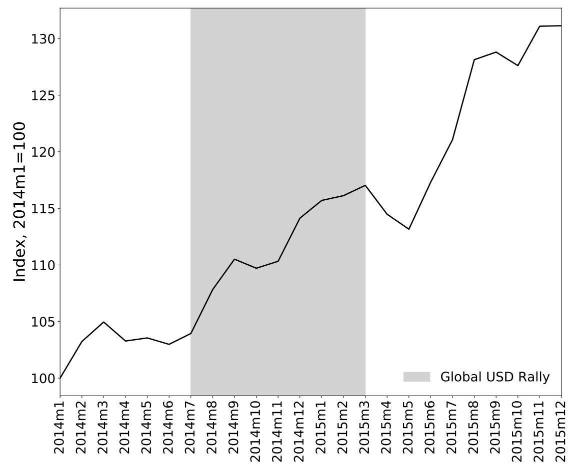
Figures 13 to 16 depict the distribution of subcategory-specific *price ratios* and *quantity ratios* for imported products compared to domestic products of the same subcategory in the four Latin American countries. Specifically, the price ratios ($\rho^T_{gt}$) are calculated by dividing a Tornqvist price index for imported products by a Tornqvist price index for domestic products, while the quantity ratios ($\sigma^T_{gt}$) are obtained by dividing a Tornqvist quantity index for imported products by a Tornqvist quantity index for domestic products. The calculation of both ratios follows the methodology described in equations (3) to (5) and (10) to (12), respectively. The figures show the distribution of these ratios across different product subcategories $g$, providing insight into the relative pricing and quantity trends for imported versus domestic goods in these countries.

Our findings for Brazil, Chile, Mexico and Peru are consistent with the findings for Colombia. Specifically, we find that the relative prices of imported products over their domestic substitutes remain fairly constant,

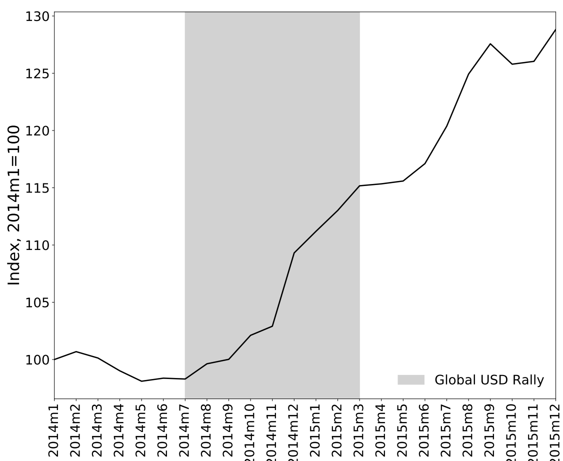
Figure 12: US dollar exchange rates, 2014-2015



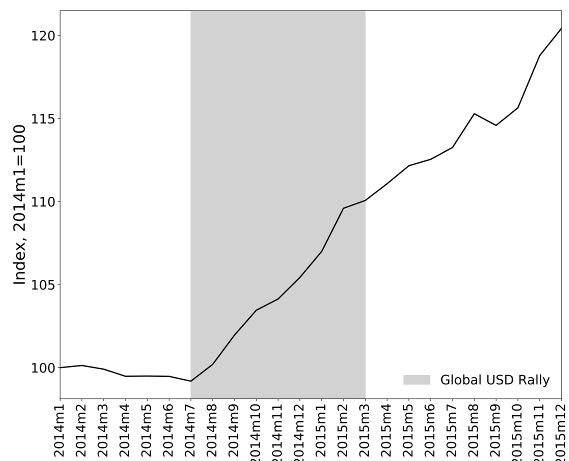

(a) Nominal USD/BRL exchange rate. Source: IMF




(b) Nominal USD/CLP exchange rate. Source: IMF



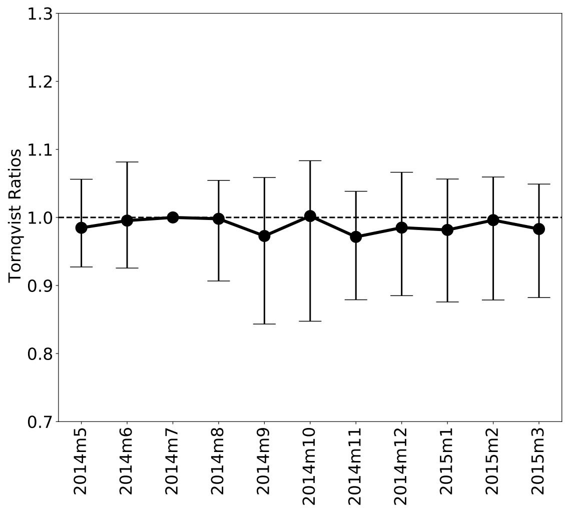

(c) Nominal USD/MXN exchange rate. Source: IMF



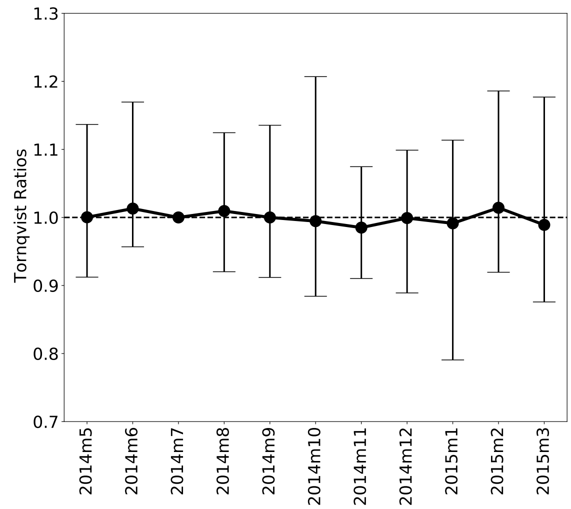

(d) Nominal USD/PEN exchange rate. Source: IMF

even in the face of the US dollar appreciation and a diverse set of countries. This contradicts the widely held notion that exchange rate movements generate relative price movements. The fact that our results are consistent across countries supports the idea that the role of the retail sector in transmitting exchange rate fluctuations to off-the-shelf prices is more complex than generally believed. In addition, our findings for Colombia provide evidence that stable relative prices do not result in large-scale expenditure switching. Importantly, we find that this result holds true for the other Latin American countries in our sample as well, which highlights the need for further research to understand the mechanisms driving the stability of relative prices across countries and over time.

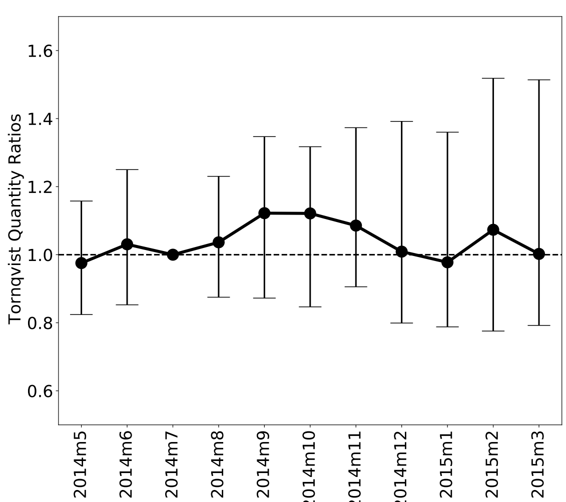
Figure 13: Distribution of price and quantity index ratios around the US dollar rally in Brazil



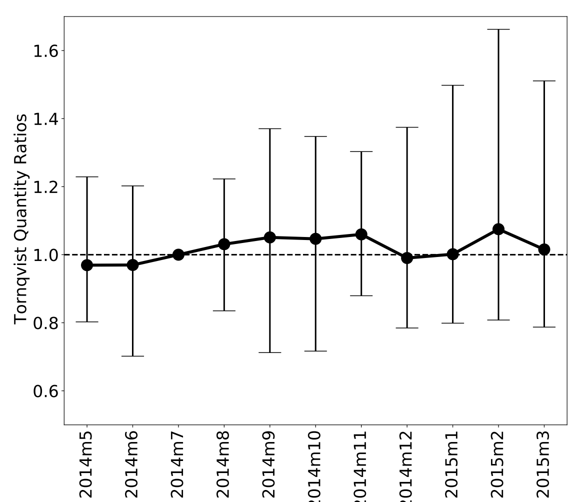

(a) Tornqvist p-ratio, static product universe




(b) Tornqvist p-ratio, dynamic product universe



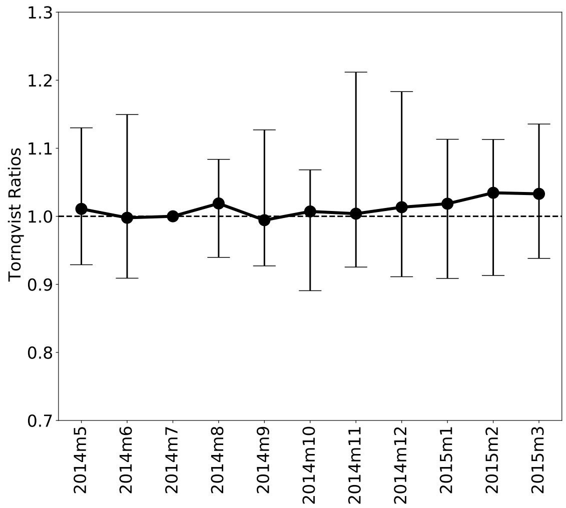

(c) Tornqvist q-ratio, static product universe



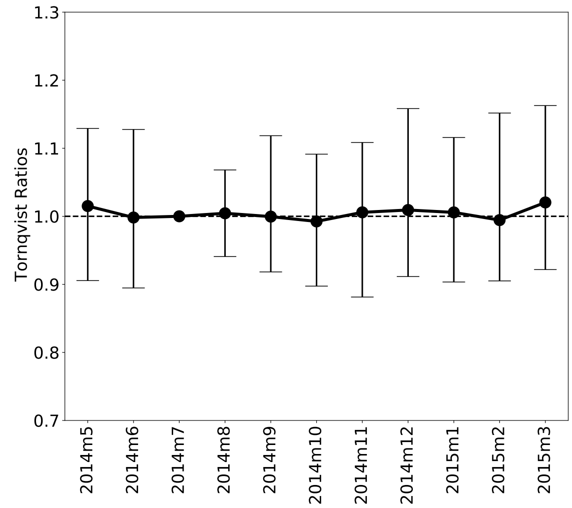

(d) Tornqvist q-ratio, dynamic product universe

**Note:** This figure illustrates the distribution of $\rho_{gt}^{T}$ and $\sigma_{gt}^{T}$ across different product subcategories $g$ for Brazil. The medians are denoted by dots. The whiskers define the 90th and 10th percentile of the data, respectively. The left column is based on the static product universe and the right column is based on the dynamic product universe. We restrict the analysis to 30 subcategories (static product universe) and 42 subcategories (dynamic product universe) for which we observe at least 5 domestic and imported products.

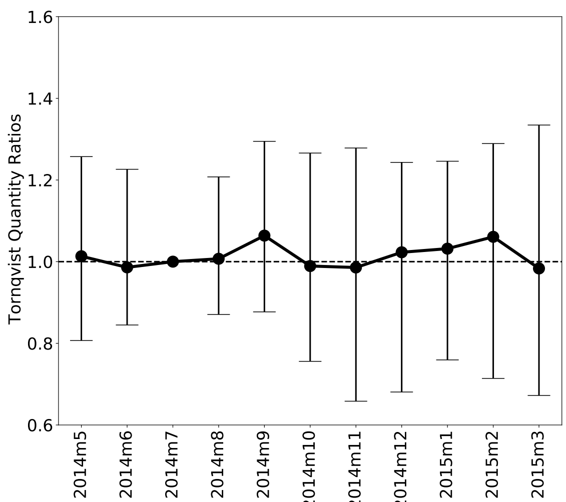
Figure 14: Distribution of price and quantity index ratios around the US dollar rally in Chile



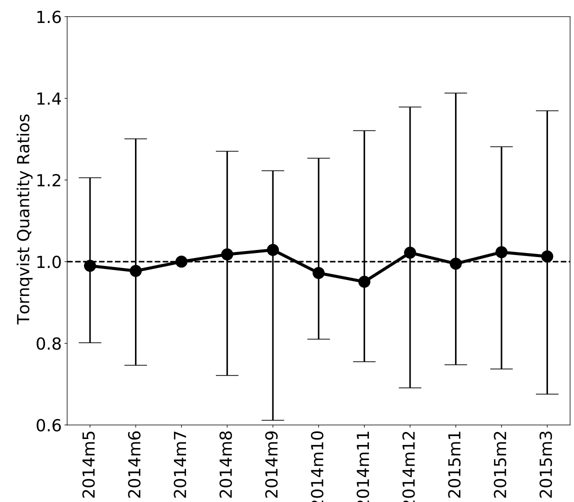

(a) Tornqvist p-ratio, static product universe




(b) Tornqvist p-ratio, dynamic product universe



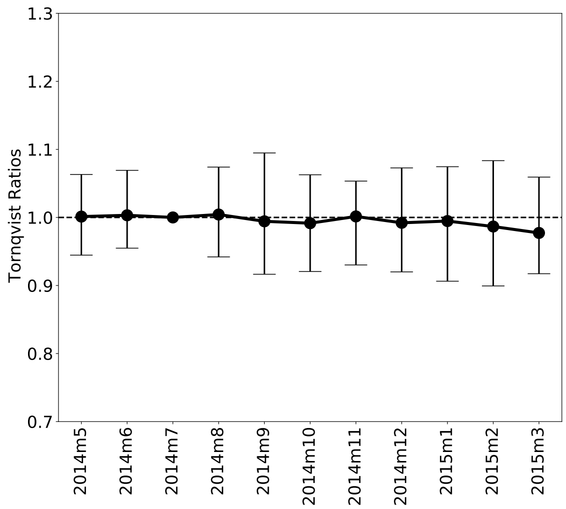

(c) Tornqvist q-ratio, static product universe



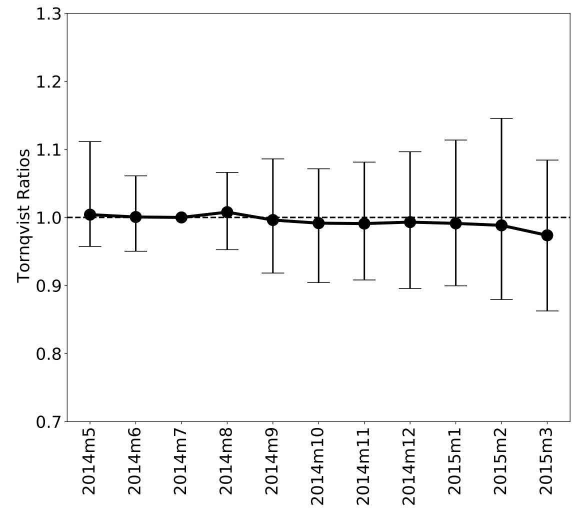

(d) Tornqvist q-ratio, dynamic product universe

**Note:** This figure illustrates the distribution of $\rho_{gt}^{T}$ and $\sigma_{gt}^{T}$ across different product subcategories $g$ for Chile. The medians are denoted by dots. The whiskers define the 90th and 10th percentile of the data, respectively. The left column is based on the static product universe and the right column is based on the dynamic product universe. We restrict the analysis to 51 subcategories (static product universe) and 60 subcategories (dynamic product universe) for which we observe at least 5 domestic and imported products.

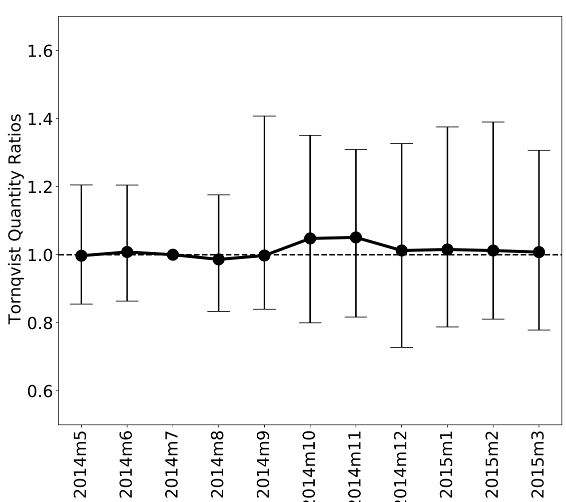
Figure 15: Distribution of price and quantity index ratios around the US dollar rally in Mexico



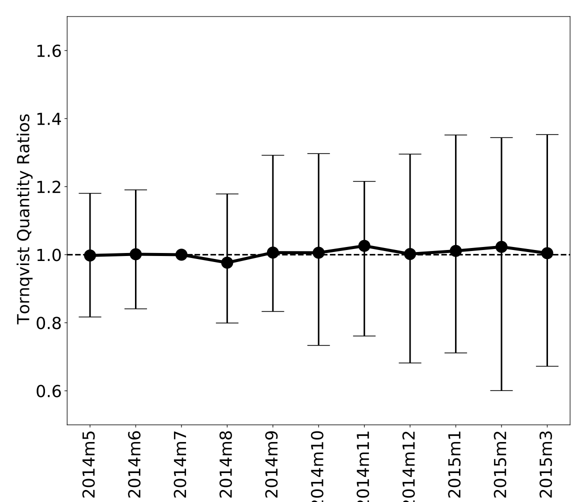

(a) Tornqvist p-ratio, static product universe




(b) Tornqvist p-ratio, dynamic product universe



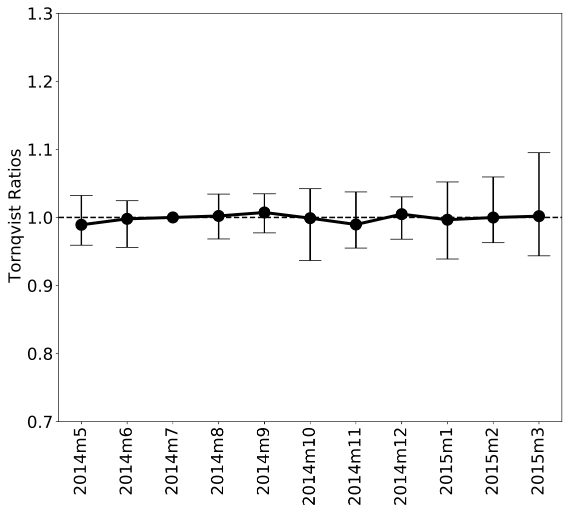

(c) Tornqvist q-ratio, static product universe



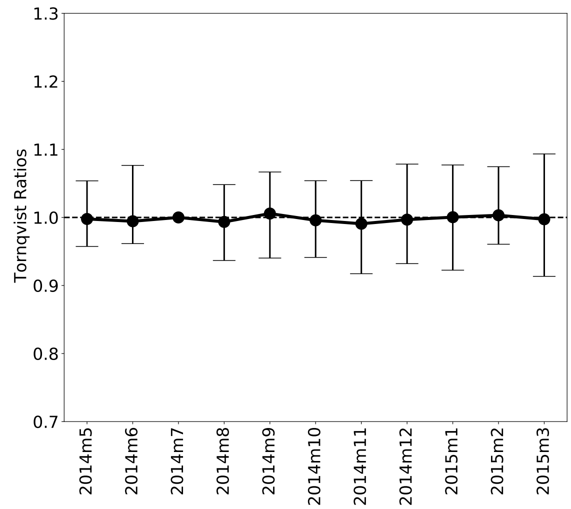

(d) Tornqvist q-ratio, dynamic product universe

**Note:** This figure illustrates the distribution of $\rho^T_{gt}$ and $\sigma^T_{gt}$ across different product subcategories $g$ for Mexico. The medians are denoted by dots. The whiskers define the 90th and 10th percentile of the data, respectively. The left column is based on the static product universe and the right column is based on the dynamic product universe. We restrict the analysis to 60 subcategories (static product universe) and 70 subcategories (dynamic product universe) for which we observe at least 5 domestic and imported products.

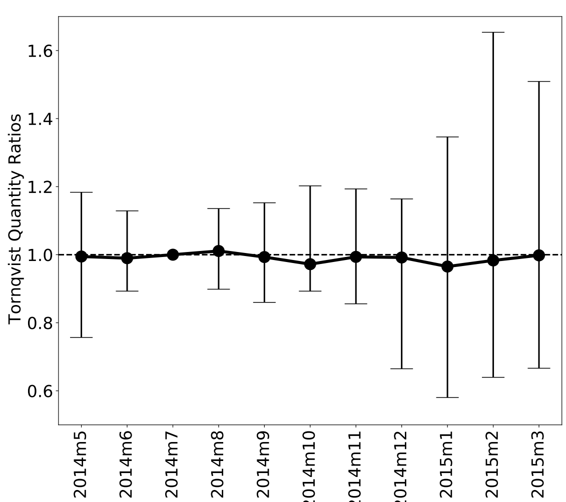
Figure 16: Distribution of price and quantity index ratios around the US dollar rally in Peru



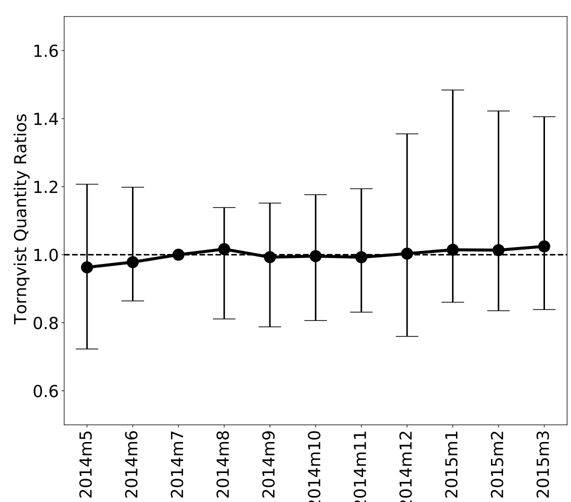

(a) Tornqvist p-ratio, static product universe




(b) Tornqvist p-ratio, dynamic product universe




(c) Tornqvist q-ratio, static product universe




(d) Tornqvist q-ratio, dynamic product universe

**Note:** This figure illustrates the distribution of $\rho_{gt}^{T}$ and $\sigma_{gt}^{T}$ across different product subcategories $g$ for Peru. The medians are denoted by dots. The whiskers define the 90th and 10th percentile of the data, respectively. The left column is based on the static product universe and the right column is based on the dynamic product universe. We restrict the analysis to 32 subcategories (static product universe) and 40 subcategories (dynamic product universe) for which we observe at least 5 domestic and imported products.

## 5.7. Summary and conclusions

There is a wide-spread conjecture that exchange rate fluctuations affect the border prices of imported products, and that – despite the dampening effect of the "retail wedge" – they influence both the aggregate price level and the price structure faced by consumers. Our empirical results question the second part of this line of arguments: While imported products may become more expensive than their domestic substitutes at the border, we do not observe this variation in relative prices at the retail level. As a consequence, the impact of exchange rate fluctuations on inflation and spending patterns may be very different from the impact that is suggested by the analysis of border prices.

More specifically, our analysis demonstrates that despite a significant depreciation of the currencies of five Latin American countries (Brazil, Chile, Colombia, Mexico, and Peru) against the US dollar, which is the dominant invoicing currency of imported products in the region, relative prices of close substitutes at the retail level remain remarkably stable. We provide evidence to support the conjecture that this stability in relative prices limits the extent of expenditure switching from imported to domestic products, even in the face of cost shocks to border prices of imported products due to a strong and exogenous US dollar rally.

Our results suggest that the role of the retail sector in transmitting exchange rate fluctuations to shelf prices faced by consumers is complex and goes beyond acting as a mere "buffer". In fact, retailers seem to have an incentive to avoid variations in relative prices. As a consequence, they accept a lower markup for imported products, which they eventually compensate by increasing the prices of *both* imported and domestic products. This conjecture is in line with recent research of Cole & Eckel (2018) who describe optimizing retailers as accounting for both relative prices *within* the shop and vis-á-vis competing retail outlets.[16] While Cole & Eckel (2018) emphasize the importance of a "multi-product firm" interpretation of the retail industry for the transmission of *tariffs*, our findings highlight the relevance of this interpretation for ERPT to consumer prices. We thus believe that a better grasp of price-setting mechanics and dynamics at the retail level is crucial for understanding the effect of exchange rate fluctuations on consumer price inflation.

[16] Further analyses with an explicit focus on retailers are provided by Besanko & Dubé & Gupta (2005) and Hellerstein (2008).

# 6. Concluding remarks

In this cumulative dissertation, I analyze the extent to which changes in the exchange rate are reflected in consumer prices, i.e. *exchange rate pass-through* (ERPT) into consumer prices, from both *micro-* and *macroscopic* perspectives. The terms 'microscopic' and 'macroscopic', which are commonly used in other disciplines such as biology or physics, distinguish between viewpoints that focus on fine details and those that consider broader, more generalized facets, respectively. In the context of ERPT, macroscopic perspectives can be understood as approaches that utilize *price aggregates*, whereas microscopic perspectives consider prices of *completely disaggregate products*. While macroscopic approaches are primarily evident in policy-oriented studies, the microscopic counterpart has become integrated into several areas of academic research following the introduction of barcode scanner technology in the 1970s (Dubois & Griffith & O'Connell, 2022).

In the literature, there appears to be a consensus that ERPT to aggregate import prices is incomplete, yet significantly more pronounced than ERPT to aggregate consumer prices (see, e.g., Burstein & Gopinath, 2014). This observation aligns with the findings of my study titled *Rethinking standard metrics: the influence of effective exchange rate selection on euro area pass-through estimates*, in which I investigate ERPT to price aggregates in the euro area since the introduction of the euro in 1999. Specifically, I estimate ERPT to import and consumer prices at 38 percent and 18 percent, respectively, after one year. These estimates are consistent with findings from recent studies focusing on the euro area, such as those by Colavecchio & Rubene (2020) and Ortega & Osbat (2020). A notable aspect of my study is the departure from conventional practices, as I challenge the traditional use of publicly available nominal effective exchange rates (NEERs) for the euro. Instead, I develop alternative NEERs based on country-specific import trade flows, as opposed to the euro area's aggregated import and export trade flows. Employing these newly constructed NEERs reveals an 8 percentage point increase in ERPT to import prices and a 7 percentage point increase in ERPT to consumer prices compared to those derived from standard euro NEERs. While these adjustments do not necessarily enhance precision, the substantial disparities underscore the critical importance of selecting appropriate euro NEER measures for accurately estimating ERPT to aggregate prices.

A common observation when utilizing more disaggregated data is the heterogeneity of ERPT across units. For instance, as pointed out by Burstein & Gopinath (2014, p.403), "ERPT estimates exhibit substantial variance across different goods." This variation inherently suggests that estimates of ERPT to aggregate prices may be prone to *aggregation bias*, a phenomenon well-documented in the macroeconomic literature. This kind of bias is theoretically formulated by Pesaran & Smith (1995), who illustrate that aggregation can potentially induce an upward bias in estimates derived from heterogeneous panels. This rationale is also adopted by Imbs et al. (2005) in their efforts to explain the purchasing power parity puzzle. Furthermore, Mumtaz & Oomen & Wang (2011) show that ERPT studies are not immune to the aggregation bias. Their study, which encompasses an analysis of the United Kingdom's import prices at both aggregate and industry levels, reveals a significant upward bias in long-run ERPT when inferred from aggregate data.

Acknowledging this criticism, I shift the focus in the subsequent three studies from aggregate price metrics to the analysis of individual prices for fully disaggregated products, utilizing a unique scanner dataset provided by Kantar, a multinational market research firm that collects market research data globally. This dataset offers in-depth transaction data on household purchases of *fast-moving consumer goods* (FMCG), such as food, beverages, alcohol, personal care, household cleaning products, and cosmetics.

The initial study utilizing this scanner dataset is titled *A microscopic analysis of UK retail price fluctuations following the Brexit vote with scanner data*. In this study, I examine UK retail price dynamics following the significant depreciation of the British pound triggered by the Brexit referendum in June 2016. This event, termed the *Brexit depreciation*, represents a rare example of an exogenous inflation shock since the outcome of the referendum came as a surprise, was not associated with macroeconomic turmoil, and since it significantly raised UK consumer prices (see, e.g., Gerstein et al., 2019, Breinlich et al., 2021, Dhingra & Sampson, 2022). Consequently, price dynamics are interpretable within the domain of ERPT. In the first part, I demonstrate that the dynamic nature of scanner data leads to fluctuating inflation rates, depending on the product selection and shifts in consumer behavior that are incorporated into the price index. Additionally, I underscore the significance of *extensive margin adjustments*, referring to price changes of newly introduced and re-appearing products. Incorporating extensive margin adjustments, I find that FMCG prices exhibited a *slight* downward movement prior to the referendum, but started to move *sharply* upward following the referendum. Following this, I show that imported products did not become significantly more expensive than their domestically produced counterparts. This finding may initially appear paradoxical, as conventional wisdom would suggest that imported products are more susceptible to fluctuations in exchange rates. Finally, I demonstrate the profound welfare and distributional implications of the depreciation shock induced by the Brexit vote on the Pound sterling. Although the inflationary impact was felt throughout all *social classes*, the magnitude of the impact notably varied between them. Specifically, the *Upper Middle Class* experienced the steepest price change, and the *Working Class* a lesser, albeit still notable, increase. Given their tighter budgets, this implies that the *Working Class* – notably major supporters of the 'Leave' campaign – were among the most impacted by the subsequent price hikes. Most alarmingly, however, is the finding that households at the lowest level of subsistence experienced high inflation (6.6 percent over the 18 months following the referendum) and thus suffered effectively the most from the Brexit vote-induced depreciation shock on the Pound sterling.

The remaining two studies focus on key findings from this aforementioned work. First, in the study titled *Anti-poor and anti-rich: Product-downgrading and the distributional effects of UK inflation in the wake of the Brexit vote* (co-authored), we examine the distributional impacts of British inflation following the Brexit depreciation. Given the strong correlation between income levels and social class affiliation, and the varying inflation rates across social classes, it is evident that the Brexit depreciation has led to *distributional effects*. While it is well-known that effective inflation rates may differ across different parts of the population due to factors such as group-specific expenditure patterns or heterogeneous price dynamics, we focus on one particular aspect that is likely to contribute to different inflation experiences: households' ability and willingness to cushion the overall impact of the price increase by engaging in *product-downgrading*, i.e. by replacing more expensive varieties of a given product type by less expensive varieties. A notable characteristic of the analysis lies in its utilization of *volume shares* in calculating price averages, as opposed to, for instance, expenditure weights, which combine information on both quantities and prices and assign greater importance to varieties with higher prices. The adoption of volume-share weighting would not have been feasible without access to such detailed, granular data. The results of our analysis suggest that, when we focus on the extent of product-downgrading, the distributional consequences of the Brexit depreciation were anti-poorest and – to some extent – anti-rich. That is because the poorest households in our sample tend to purchase the most affordable varieties within narrowly defined product types, thus limiting their ability to further switch to more affordable varieties during the inflationary period following the Brexit referendum. In contrast, middle income-households have more flexibility to adjust their purchasing habits to evade inflation, resulting in lower inflation rates compared to the poorest households. Wealthier households, despite having the capacity to substitute away from more expensive varieties, apparently choose not to, leading them to encounter inflation rates higher than those experienced by poor households, but still below the ones experienced by poorest households. We believe that the results we have presented add an important insight on the distributional effects of inflation, which – for lack of appropriate data – had to be neglected so far.

Second, in the study titled *Retail prices in Latin America during the 2014-2015 US dollar rally: a microscopic perspective using scanner data* (co-authored), we investigate whether the parallel price evolution of similar imported and domestic products observed in the UK in 2016 and 2017 is also evident in other regions across the globe. We focus on the *US dollar rally* that started in mid-2014, and that resulted in a substantial nominal appreciation of the US dollar against most other currencies in the world. This appreciation was driven by markets' expectations of a tighter monetary policy and accelerating growth in the US, and thus exogenous to the countries whose currencies were affected. We focus on Colombia and four other Latin American countries (Brazil, Chile, Mexico and Peru) since the overwhelming share of these countries' imports are priced in US dollars – i.e. prices of imported products should have been affected particularly strongly by the US dollar rally. Focusing on Colombia, our primary country of interest, we observe that the response of prices to the US dollar rally was both delayed and subdued. Specifically, it took approximately six months for the price indices of imported products to begin rising, and the modest increase in prices of a few percent stands in stark contrast to the 40 percent depreciation of the Colombian peso against the US dollar. Furthermore, and perhaps even more surprisingly, we discover that prices of imported products and domestically produced counterparts of the same type – i.e. domestically produced close substitutes – moved in parallel, such that the ratio of imported product prices over domestic product prices barely changed. This pattern was consistent across the other Latin American countries in our sample as well. We interpret this parallel evolution as indicative of a more proactive role played by the retail sector than generally believed. Moreover, in the absence of significant relative price adjustments, we do not anticipate a substantial shift in consumer spending from imported to domestic products. Our analysis of expenditure switching and quantity reactions supports this conjecture. Consequently, our research underscores the importance of gaining a deeper understanding of the mechanics and dynamics of price-setting at the retail level for understanding the effect of exchange rate fluctuations on consumer price inflation.

In conclusion, this dissertation emphasizes the importance of selecting appropriate NEER measures for examining ERPT from a macroscopic perspective. Furthermore, I hope to have made valuable contributions to the growing field of microscopic research centered on the analysis of completely disaggregate products.

# 7. Bibliography


Ampudia, Miguel & Michael Ehrmann & Georg Strasser (2023). *The effect of monetary policy on inflation heterogeneity along the income distribution.* Working Paper 1124. Bank for International Settlements.

Argente, David & Munseob Lee (2021). “Cost of Living Inequality During the Great Recession”. In: *Journal of the European Economic Association* 19.2, 913–952.

Arsova, Antonia (2021). “Exchange rate pass-through to import prices in Europe: a panel cointegration approach”. In: *Empirical Economics* 61.1, 61–100.

Auer, Raphael & Ariel Burstein & Sarah M. Lein (2021). “Exchange Rates and Prices: Evidence from the 2015 Swiss Franc Appreciation”. In: *American Economic Review* 111.2, 652–686.

Bailliu, Jeannine & Eiji Fujii (2004). *Exchange Rate Pass-Through and the Inflation Environment in Industrialized Countries: An Empirical Investigation.* Staff Working Paper. Bank of Canada.

Bandt, Olivier de & Tovonony Razafindrabe (2014). “Exchange rate pass-through to import prices in the Euro-area: A multi-currency investigation”. In: *International Economics* 138, 63–77.

Bems, Rudolfs & Julian di Giovanni (2016). “Income-Induced Expenditure Switching”. In: *American Economic Review* 106.12, 3898–3931.

Bennett, Jeannette N. (2022). *Beyond Inflation Numbers: Shrinkflation and Skimpflation.* Page One Economics. Federal Reserve Bank of St. Louis.

Besanko, David & Jean-Pierre Dubé & Sachin Gupta (2005). “Own-Brand and Cross-Brand Retail Pass-Through”. In: *Marketing Science* 24.1, 123–137.

Bonadio, Barthélémy & Andreas M. Fischer & Philip Sauré (2019). “The Speed of Exchange Rate Pass-Through”. In: *Journal of the European Economic Association* 18.1, 506–538.

Boz, Emine & Camila Casas & Georgios Georgiadis & Gita Gopinath & Helena Le Mezo & Arnaud Mehl & Tra Nguyen (2022). “Patterns of Invoicing Currency in Global Trade: New Evidence”. In: *Journal of International Economics* 136.

Boz, Emine & Gita Gopinath & Mikkel Plagborg-Møller (2017). *Global Trade and the Dollar.* Working Paper 23988. National Bureau of Economic Research.

Braun, Rahel & Sarah M. Lein (2021). “Sources of Bias in Inflation Rates and Implications for Inflation Dynamics”. In: *Journal of Money, Credit and Banking* 53.6, 1553–1572.

Breinlich, Holger & Elsa Leromain & Dennis Novy & Thomas Sampson (2021). “The Brexit Vote, Inflation and U.K. Living Standards”. In: *International Economic Review* 63.1, 63–93.

Broadbent, Ben (2017). *Brexit and the pound.* Speech given at Imperial College, London. Bank of England.

Broda, Christian & John Romalis (2009). *The Welfare Implications of Rising Price Dispersion.* Working Paper. University of Chicago.

Burstein, Ariel & Martin Eichenbaum & Sergio Rebelo (2005). “Large Devaluations and the Real Exchange Rate”. In: *Journal of Political Economy* 113.4, 742–784.

Burstein, Ariel & Gita Gopinath (2014). "International Prices and Exchange Rates". In: *Handbook of International Economics*. Elsevier, 391–451.

Cage, Robert & Thesia Garner (2002). *Constructing Household Specific Consumer Price Indexes: An Analysis of Different Techniques and Methods*. Working Paper 354. Bureau of Labor Statistics.

Campa, José & Linda Goldberg (2005). "Exchange Rate Pass-Through into Import Prices". In: *Review of Economics and Statistics* 87.4, 679–690.

Campa, José & Jose M. González Mínguez (2006). "Differences in exchange rate pass-through in the euro area". In: *European Economic Review* 50.1, 121–145.

Cavallo, Alberto & Brent Neiman & Roberto Rigobon (2014). "Currency Unions, Product Introductions, and the Real Exchange Rate". In: *Quarterly Journal of Economics* 129.2, 529–596.

Cheikh, Nidhaleddine Ben & Christophe Rault (2017). *Investigating First-Stage Exchange Rate Pass-Through: Sectoral and Macro Evidence from Euro Area Countries*. Working Paper 6366. CESifo.

Chessa, Antonio G. (2016a). *A Comparison of Price Index Methods for Scanner Data*. Working Paper. Eurostat.

— (2016b). "A new methodology for processing scanner data in the Dutch CPI". In: *Eurostat Review of National Accounts and Macroeconomic Indicators* 1, 49–69.

Chessa, Antonio G. & Johan Verburg & Leon Willenborg (2017). *A New Methodology for Processing Scanner Data in the Dutch CPI*. Working Paper. Bundesbank.

Coibion, Olivier & Yuriy Gorodnichenko & Gee Hee Hong (2015). "The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications". In: *American Economic Review* 105.3, 993–1029.

Colavecchio, Roberta & Ieva Rubene (2020). *Non-linear Exchange Rate Pass-Through to Euro Area Inflation: A Local Projection Approach*. Working Paper 2362. European Central Bank.

Cole, Matthew T. & Carsten Eckel (2018). "Tariffs and Markups in Retailing". In: *Journal of International Economics* 113.C, 139–153.

Colicev, Anatoli & Joris Hoste & Jozef Konings (2022). *The Impact of a Large Depreciation on the Cost of Living of Rich and Poor Consumers*. Discussion Paper 16869. Centre for Economic Policy Research.

Comunale, Mariarosaria (2015). *Financial Cycle Measures for 41 Countries: A New Database*. Working Paper. Bank of Lithuania.

Comunale, Mariarosaria & Davor Kunovac (2017). *Exchange Rate Pass-Through in the Euro Area*. Occasional Paper Series Working Paper 2003. European Central Bank.

Constâncio, Vítor (2017). *Understanding and Overcoming Low Inflation*. Remarks at the Conference on "Understanding Inflation: Lessons from the Past, Lessons for the Future?". European Central Bank.

Corsetti, Giancarlo & Meredith Crowley & Lu Han (2022). "Invoicing and the Dynamics of Pricing-to-market Evidence from UK Export Prices around the Brexit Referendum". In: *Journal of International Economics* 135(C).

Corsetti, Giancarlo & Meredith A. Crowley & Lu Han & Huasheng Song (2023). *Markets and markups: a new empirical framework and evidence on exporters from China*. Working Paper 2023/27. Refugee Studies Centre.

Corsetti, Giancarlo & Luca Dedola (2005). "A Macroeconomic Model of International Price Discrimination". In: *Journal of International Economics* 67.1, 129–155.

Corsetti, Giancarlo & Luca Dedola & Sylvain Leduc (2008). "High Exchange-Rate Volatility and Low Pass-Through". In: *Journal of Monetary Economics* 55.6, 1113–1128.

Cravino, Javier & Andrei A. Levchenko (2017). "The Distributional Consequences of Large Devaluations". In: *American Economic Review* 107.11, 3477–3509.

Crawford, Ian & Zoe Oldfield (2002). *Distributional aspects of inflation*. Working Paper. Institute for Fiscal Studies.

Daalmans, Jacco (2022). *Multilateral indices and the relaunch problem: Product clustering and alternative solutions*. Discussion Paper. Centraal Bureau voor de Statistiek Netherlands.

DellaVigna, Stefano & Matthew Gentzkow (2019). "Uniform Pricing in U.S. Retail Chains". In: *Quarterly Journal of Economics* 134.4, 2011–2084.

Dhingra, Swati & Thomas Sampson (2022). "Expecting Brexit". In: *Annual Review of Economics* 14.1, 495–519.

Dieppe, Alistair & Georgios Georgiadis & Martino Ricci & Ine Robays & Björn Roye (2018). "ECB-Global: Introducing the ECB's global macroeconomic model for spillover analysis". In: *Economic Modelling* 72.

Diewert, W. Erwin & Peter von der Lippe (2010). "Notes on Unit Value Index Bias". In: *Jahrbücher für Nationalökonomie und Statistik* 230.6, 690–708.

Dornbusch, Rüdiger (1987). "Exchange Rates and Prices". In: *American Economic Review* 77.1, 93–106.

Dubois, Pierre & Rachel Griffith & Martin O'Connell (2022). "The Use of Scanner Data for Economics Research". In: *Annual Review of Economics* 14.1.

Eichenbaum, Martin & Nir Jaimovich & Sergio Rebelo (2011). "Reference Prices, Costs, and Nominal Rigidities". In: *American Economic Review* 101.1, 234–262.

Eurostat (2022). *Guide on Multilateral Methods in the Harmonised Index on Consumer Prices (HICP) - 2022 Edition*. Manual.

Fajgelbaum, Pablo D. & Amit K. Khandelwal (2016). "Measuring the Unequal Gains from Trade". In: *Quarterly Journal of Economics* 131.3, 1113–1180.

Faruqee, Hamid (2006). *Exchange Rate Pass-Through in the Euro Area*. Staff Paper 53/1. International Monetary Fund, 63–88.

Fidora, Michael & Martin Schmitz (2020). *The ECB's enhanced effective exchange rate measures*. Economic Bulletin Boxes 6. European Central Bank.

Frankel, Jeffrey & David Parsley & Shang-Jin Wei (2011). "Slow Pass-through Around the World: A New Import for Developing Countries?" In: *Open Economies Review* 23.2, 213–251.

Frankel, Jeffrey & Andrew Rose (1996). “Currency Crashes in Emerging Markets: An Empirical Treatment”. In: *Journal of International Economics* 41.3, 351–366.

Gaggl, Paul (2009). “The Role of Exchange Rate Movements for Prices in the Euro Area”. In: *Monetary Policy and the Economy, Oesterreichische Nationalbank* 2.

Garner, Thesia I. & Javier Ruiz-Castillo & Mercedes Sastre (2003). “The Influence of Demographics and Household-Specific Price Indices on Consumption-Based Inequality and Welfare: A Comparison of Spain and the United States”. In: *Southern Economic Journal* 70.1, 22–48.

Georgiadis, Georgios & Johannes Gräb & Makram Khalil (2020). *Global value chain participation and exchange rate pass-through*. Discussion Paper 67. Deutsche Bundesbank.

Gerstein, Neil & Bart Hobijn & Fernanda Nechio & Adam Shapiro, et al. (2019). *The Brexit price spike*. Economic Letter. Federal Reserve Bank of San Francisco.

Goetz, Daniel & Alexander Rodnyansky (2023). “Exchange Rate Shocks and Quality Adjustments”. In: *Review of Economics and Statistics* 105.1, 86–100.

Goldberg, Pinelopi K. & Michael M. Knetter (1997). “Goods Prices and Exchange Rates: What Have We Learned?” In: *Journal of Economic Literature* 35.3, 1243–1272.

Gopinath, Gita & Emine Boz & Camila Casas & Federico J. Díez & Pierre-Olivier Gourinchas & Mikkel Plagborg-Møller (2016). *Dominant Currency Paradigm*. Working Paper 22943. National Bureau of Economic Research.

Gopinath, Gita & Emine Boz & Camila Casas & Federico J. Diez & Pierre-Olivier Gourinchas & Mikkel Plagborg-Møller (2020). “Dominant Currency Paradigm”. In: *American Economic Review* 110.3, 677–719.

Gopinath, Gita & Oleg Itskhoki (2021). *Dominant Currency Paradigm: A Review*. Working Paper 29556. National Bureau of Economic Research.

Gopinath, Gita & Oleg Itskhoki & Roberto Rigobon (2010). “Currency Choice and Exchange Rate Pass-Through”. In: *American Economic Review* 100.1, 304–36.

Graf, Brian, ed. (2020). *Consumer Price Index Manual: Concepts and Methods*. Manuals & Guides. Publication Date: 19 Nov 2020. International Monetary Fund.

Gürer, Eren & Alfons Weichenrieder (2020). “Pro-rich inflation in Europe: Implications for the measurement of inequality”. In: *German Economic Review* 21.

Ha, Jongrim & Anna Ivanova & Franziska Lieselotte Ohnsorge & Derya Filiz Unsal Portillo Ocando (2019). *Inflation: Concepts, Evolution, and Correlates*. The World Bank.

Hagemann, Robert P. (1982). “The Variability of Inflation Rates Across Household Types”. In: *Journal of Money, Credit and Banking* 14.4, 494–510.

Hahn, Elke (2003). *Pass-through of external shocks to euro area inflation*. Working Paper 243. European Central Bank.

Harms, Philipp & Mathias Hoffmann & Christina Ortseifer (2015). "The Home Bias in Equities and Distribution Costs". In: *Scandinavian Journal of Economics* 117.1, 983–1018.

Hellerstein, Rebecca (2008). "Who Bears the Cost of a Change in the Exchange Rate? Pass-through Accounting for the Case of Beer". In: *Journal of International Economics* 76.1, 14–32.

Hobijn, Bart & David Lagakos (2005). "Inflation Inequality in the United States". In: *Review of Income and Wealth* 51.4, 581–606.

Imbs, Jean & Haroon Mumtaz & Morten O. Ravn & Hélène Rey (2005). "PPP Strikes Back: Aggregation and the Real Exchange Rate". In: *Quarterly Journal of Economics* 120.1, 1–43.

Jaravel, Xavier (2018). "The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector". In: *Quarterly Journal of Economics* 134.2, 715–783.

— (2021). "Inflation Inequality: Measurement, Causes, and Policy Implications". In: *Annual Review of Economics* 13.1, 599–629.

Kaminsky, Graciela & Saul Lizondo & Carmen M. Reinhart (1998). *Leading Indicators of Currency Crises.* Staff Paper 45/1. International Monetary Fund.

Kaplan, Greg & Sam Schulhofer-Wohl (2017). "Inflation at the household level". In: *Journal of Monetary Economics* 91.C, 19–38.

Kenny, Geoff & Donal Mcgettigan (1998). "Exchange rates and import prices for a small open economy: the case of Ireland". In: *Applied Economics* 30.9, 1147–1155.

Landolfo, Luigi (2007). *Modeling the impact of external factors on the euro area's HICP and real economy: a focus on pass-through and the trade balance*. Working Paper 789. European Central Bank.

McCarthy, Jonathan (2007). "Pass-through of Exchange Rates and Import Prices to Domestic Inflation in Some Industrialized Economies". In: *Eastern Economic Journal* 33.4, 511–537.

Michael, Robert T. (1979). "Variation Across Households in the Rate of Inflation". In: *Journal of Money, Credit and Banking* 11.1, 32–46.

Misztal, Piotr (2010). "The Phenomenon of Incomplete Exchange Rate Pass-Through to Prices in the Euro Area". In: *EuroEconomica* 24, 36–47.

Möhrle, Sascha & Timo Wollmershäuser (2021). "Zu den Verteilungseffekten der derzeit hohen Inflationsraten". In: *ifo Schnelldienst Digital* 2.16, 01–06.

Mumtaz, Haroon & Ozlem Oomen & Jian Wang (2011). *Exchange rate pass-through into U.K. import prices: evidence from disaggregated data*. Staff Paper 6. Federal Reserve Bank of Dallas.

Nakamura, Emi & Jón Steinsson (2012). "Lost in Transit: Product Replacement Bias and Pricing to Market". In: *American Economic Review* 102.7, 3277–3316.

Nakamura, Emi & Dawit Zerom (2010). "Accounting for Incomplete Pass-Through". In: *Review of Economic Studies* 77.3, 1192–1230.

Obstfeld, Maurice & Kenneth Rogoff (1995). "Exchange Rate Dynamics Redux". In: *Journal of Political Economy* 103.3, 624–660.

Office for National Statistics (2023). *Distribution of UK household disposable income, financial year ending 2022*. Statistical bulletin. URL: https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth.

Orhun, A. Yesim & Mike Palazzolo (2019). "Frugality Is Hard to Afford". In: *Journal of Marketing Research* 56.1, 1–17.

Ortega, Eva & Chiara Osbat (2020). *Exchange Rate Pass-Through in the Euro Area and EU Countries*. Occasional Paper Series Working Paper 241. European Central Bank.

Osbat, Chiara & Yiqiao Sun & Martin Wagner (2021). *Sectoral exchange rate pass-through in the euro area*. Working Paper 2634. European Central Bank.

Özyurt, Selin (2016). *Has the exchange rate pass through recently declined in the euro area?* Working Paper 1955. European Central Bank.

Pesaran, M. Hashem & Ron Smith (1995). "Estimating long-run relationships from dynamic heterogeneous panels". In: *Journal of Econometrics* 68.1, 79–113.

Porto, Guido G. (2006). "Using survey data to assess the distributional effects of trade policy". In: *Journal of International Economics* 70.1, 140–160.

Rueffer, Rasmus & Filippo di Mauro & Irina Bunda (2008). *The changing role of the exchange rate in a globalised economy*. Occasional Paper Series Working Paper 94. European Central Bank.

Schmitz, Martin & Maarten Clercq & Michael Fidora & Bernadette Lauro & Cristina Pinheiro (2012). *Revisting the Effective Exchange Rates of the Euro*. Occasional Paper Series Working Paper 134. European Central Bank.

Schröder, Michael & Felix Hüfner (2002). *Exchange rate pass-through to consumer prices: a European perspective*. Discussion Paper 02-20. Leibniz Centre for European Economic Research.

Shambaugh, Jay (2008). "A new look at pass-through". In: *Journal of International Money and Finance* 27.4, 560–591.

# CV of Mark Ruszel

## Personal Information

Address: Am Gonsenheimer Spieß 2, 55122 Mainz
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Phone: +4915771334269
Citizenship: German
Date of Birth: May 29, 1993
Place of Birth: Mainz, Germany
Marital Status: Married
Children: One daughter

## Work Experience

Scientific Staff Member — Apr 2024 - Present

I am currently employed at DESTATIS (Federal Statistical Office of Germany) in the Consumer Prices Department. In my role as a Scientific Staff Member, I am responsible for evaluating the system solution for calculating the Consumer Price Index (CPI) and the Harmonized Index of Consumer Prices (HICP), particularly with regard to the technical requirements for index calculation.

Research Associate and PhD Student — Jul 2018 - Mar 2024

I was pursuing my PhD in the field of International Economics under the supervision of Prof. Philipp Harms at the Johannes Gutenberg-University Mainz. As a research associate, I actively contributed to various lectures and seminars on topics related to International Economics, Macroeconomics and Monetary Policy.

Data Analyst — Sep 2016 - Jul 2018

During my Master's studies, I worked as a data analyst on projects led by Prof. Harms that resulted in successful publications. In addition to my project-specific tasks, I took the initiative to develop a comprehensive macroeconomic panel database encompassing numerous countries worldwide. This database served as a valuable resource for multiple projects.

## Education

| | |
|---|---|
| Jul 2018 - July 2024 | PhD in the field of International Economics at Johannes Gutenberg-University Mainz |
| Jul 2019 - Aug 2019 | Financial Programming and Policies, Part 1: Macroeconomic Accounts and Analysis. A online course of study offered by the International Monetary Fund (Certified) |
| Apr 2016 - Mar 2018 | Master's Degree (M.Sc. in International Economics and Public Policy) at Johannes Gutenberg-University Mainz (GPA: 1.3/Master Thesis: 1.0) |
| Oct 2012 - Apr 2016 | Bachelor's Degree (B.Sc. in Economics) at Johannes Gutenberg-University Mainz (GPA: 1.9/Bachelor Thesis: 1.0) |
| 2004 - Mar 2012 | High School at Gymnasium Nieder-Olm |

## Volunteer Work

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|---|---|
| Dec 2015 - Feb 2017 | Volunteer at the Nieder-Ramstädter Diakonie to relieve families with impaired children |

## Scholarship

Oct 2017 - Oct 2018 Deutschlandstipendium

## Skills

| | |
|---|---|
| Languages | Proficient user of German (native) and English. Basic user of Polish (my wife´s native language) |
| Programming languages | Python and Stata (4+ years of experience), R and Matlab (1+ years of experience) |
| Other systems | LaTex and Microsoft Office (5+ years of experience) |

## Reference

For further information or to gain additional insight into my skills and qualifications, please feel free to reach out to Professor Philipp Harms: LsHarms@uni-mainz.de