The impact of technological age

An empirical analysis of technological change induced human capital depreciation and its influence on wages and the likelihood to leave an occupation

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Abstract

This analysis establishes the novel concept of technological age as a measure of occupation specific technologically induced human capital depreciation. The hypothesis is that technological age makes workers less efficient in their adoption of new technologies and leads to lower wages or workers leaving their occupations. Therefore, the analysis estimates the impact of technological age on wages and on the probability that workers leave their occupations. To measure technological age, the analysis uses the “Employment Survey of the Working Population on Qualification and Working conditions in Germany” dataset to estimate technological change for 28 occupations in the timeframe 1979-2006. This occupation specific technological change is then used to estimate an individual technological age for 971,510 individuals in the dataset “Sample of Integrated Labor Market Biographies Description.”

As hypothesized, technological age has a negative and significant impact on wages in most occupations during the sample period. Alas, when looking at subsample estimations, it becomes clear that technological age has a positive impact on wages in the timeframe from 1979-1999 and that technological age only has a negative impact on wages in the timeframe from 2000-2006. Furthermore, technological age makes workers more likely to leave their occupations in most occupations during the sample period. Yet again, when looking at sub sample periods, technological age makes workers more likely to leave their occupations during the years 1979-1999 and less likely during the years 2000-2006. Technological age surprisingly always has a more negative impact in less technologically intensive occupations. Workers in less technologically intensive occupations are affected more by the wage effect of technological age and workers in less technologically intensive occupations are more likely to leave their occupations due to technological age. This is true for the entire sample period as well as the sub sample timeframes.

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Abbreviations:

BIBB Data	The dataset “Sample of integrated labor market biographies”, of the “Institut für Arbeitsmarkt und Berufsforschung”
SIAB Data	The dataset “Sample of integrated labor market biographies”, of the “Institut für Arbeitsmarkt und Berufsforschung”
KldB88	“Klassifikation der Berufe 88” (Classification of Occupations 88)
KldB2010	Classification of Occupations 2010 (“Klassifikation der Berufe 2010”)
W_93	Industry classification 93 (“Wirtschaftszweigklassifizierung 93”)
overall sample	describing the sample period of 1979-2006
subsample 79	describing the subsample period of 1979-1989 of the *overall sample*
subsample 90	describing the subsample period of 1990-1999 of the *overall sample*
subsample 00	describing the subsample period of 2000-2006 of the *overall sample*

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1 Introduction

The last few decades have been hosting two coinciding cultural phenomena: aging first world societies[1] and information technology based technological change[2]. Especially computers, which are relevant in almost every occupation today, but which were generally irrelevant in the 1970's[3] have changed work and everyday life. Labor market and socio-economic data available for the timeframe of the introduction of computer technology make detailed observation how introducing new technology can lead to technology specific human capital depreciation possible. This process of technology specific human capital depreciation is further explored and called "**technological aging"** in this analysis. Furthermore, the impact of "**technological age"** on wages and on the likelihood of changing occupations is uncovered. Following, this introduction gives a detailed description of the aging of first world societies and the process of technological adoption before outlining the next steps of the thesis.

On the one hand, the last decades have given birth to an aging society in many first world countries. The reasons are manifold and range from lower birth rates to higher life expectancy[4]. *Figure 1* shows the median age of the population in Germany starting in 1950 and estimating median age until 2050 with a strikingly obvious steep increase in median age starting around 1970. While this general increase slows down around 2015, the median age in Germany is still expected to increase further until 2050. Furthermore, without a doubt the general aging of society has also led to a growing share of older workers. This general aging of the workforce comes with many unique challenges and opportunities, one of them connected with the vast amount of technological change the world has experienced over the last years.

[1] United Nations, Report on World Population Ageing, (2015)
[2] Technological change is well discussed in the literature. Card and DiNardo, (2002) give a nice overview of technological change.
[3] For a more in depth look at occupation's computer usage refer to *5.1.4 Technological progression according to BIBB Data*
[4] Wan et al (2016) give an overview over world population aging.

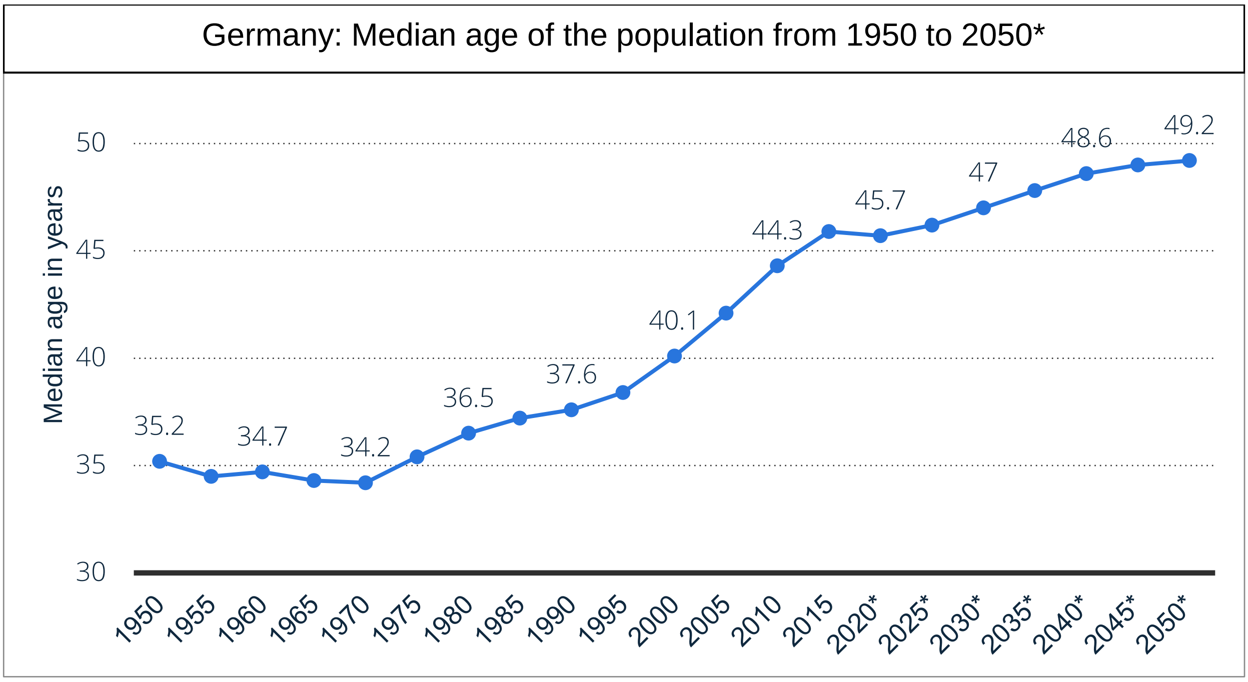

Figure 1: *Germany: Median age of the population from 1950 to 2050**

*Note: Median age of the German Population according to United Nations (2019). Years with * are estimated.*

Around the same timeframe when first world societies started to age, the world has started to see tremendous technological changes. One of the most iconic and indeed influential phenomena was the introduction of computers. In 1980, MS-Dos was introduced. The IBM personal computer followed in 1981[5]. Ever since, new inventions, iterations and uses of computers, the internet and computing devices have led from the first PCs to smart phones, smart watches, and smart homes. These innovations have not only deeply changed everyday life but also maybe even more so the way companies operate and what companies expect of their employees. *Figure 2* shows the share of German private households owning a computer from 2000-2019, while *Figure 3* shows the share of persons employed using a computer with internet access 2005-2019 in Germany and the EU. Both figures show a large degree of technologization and, furthermore, ongoing adoption of the technology of computers. Additionally, *Figure 2* shows that even within the technology of computers there was yet more change. Stationary PCs, which were present in about 60% of the households around 2010 start declining in use while mobile PCs see more and more use and could be found in over

[5] Card and DiNardo (2002)

80% of German households by 2019. Additionally, by 2020 more households own a tablet than own a computer in Germany. Similarly, *Figure 3* shows that technologization is still ongoing in the workplace as well.

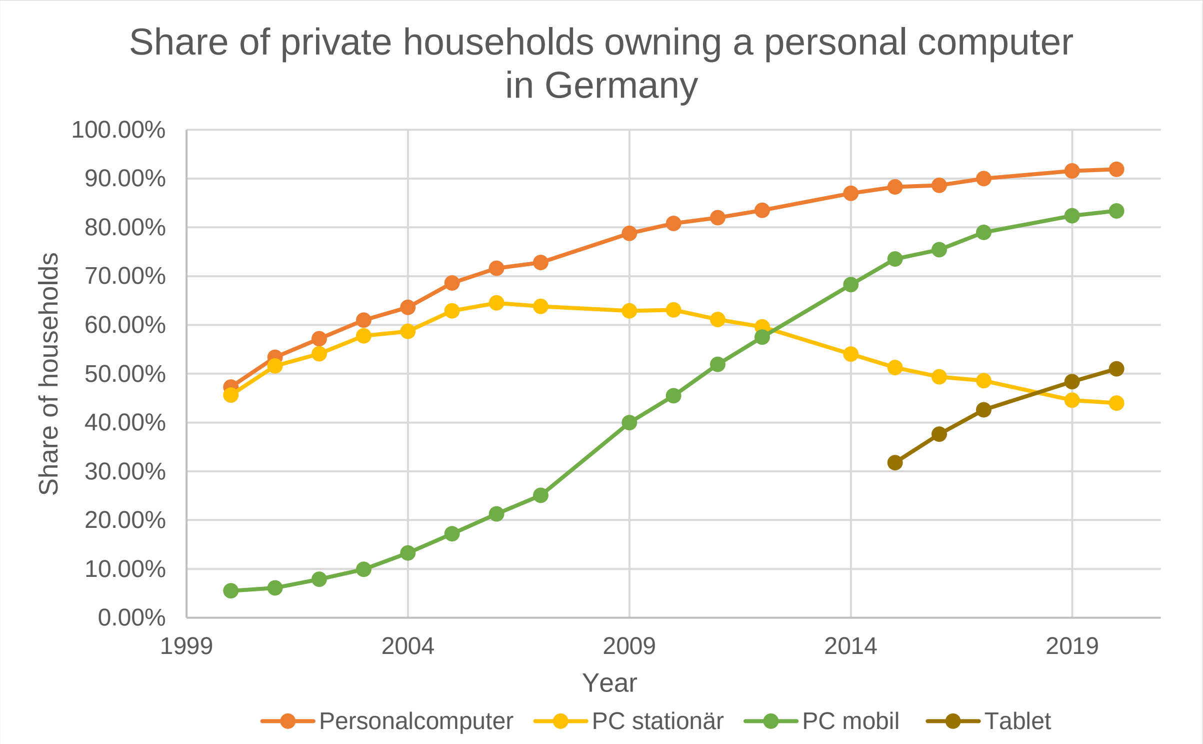

Figure 2: *Share of private households owning a personal computer in Germany*

Note: Share of private households owning a personal computer in Germany according to Statistisches Bundesamt (2021). Observations owning a personal computer is split into owning a stationary and mobile PC, owning a tablet is a new set of observations.

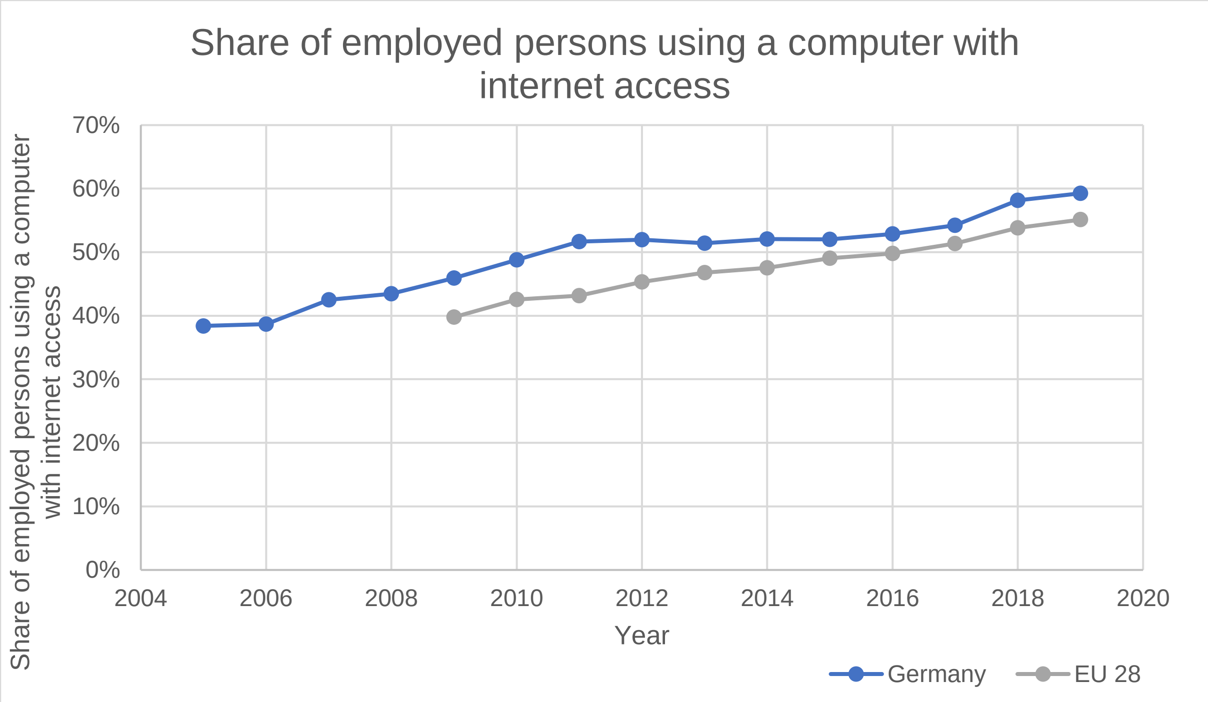

Figure 3: *Share of employed persons using a computer with internet access*

Note: Share of employed persons using a computer with internet access according to the Organisation for Economic Co-Operation and Development (OECD) (2021) in Germany and in the EU 28.

These technological innovations lead to a case where some workers still remember doing their work on a typewriter or being taught how to complete their work with tools many people entering the labor force now would not even recognize. Offices, workplaces, and production facilities now are in many cases not even remotely comparable to their counterparts forty years ago[6]. Naturally, company's production methods or means of conducting their business have changed through more than the use of computers or computing power, yet it is undeniable that the workplace in 1980 in many cases does not resemble the workplace in 2020.

An interesting aspect of change in technology is that for people entering the labor force today, levels of technology nowadays are perfectly normal. Workers entering the labor force now have grown up in a world that uses computers and the internet, where cell phones and smartphones are nothing much to think further about. This phenomenon is similar for every cohort entering the labor market across time. Children and

[6] Bresnahan et al (1996) and Bresnahan et al (2002) give some insight into how workplaces have changed.

teenagers grow up with the newest technology has to offer as part of their normal world. Today, children in school own smartphones, use TikTok, Snapchat and Instagram and do not think much when they are chatting or video calling friends that live hundreds or thousands of miles away. They do not have to learn how to use new technology as they use it as part of their everyday environment. Each cohort easily adapts to their certain level of technology they grew up using. *Figure 4* shows computer users in Germany from 2008-2017 by age group, while *Figure 5* shows the share of smartphone users in Germany by age group. In both figures, it is apparent, that the younger generations are much faster in adopting new technologies. Furthermore, one can clearly see that the older people are, the slower they become in adopting to new technologies. In 2017, barely 50% of all people 65 years and older used a computer, in 2016 only 44% of all those 55 years and older used a smartphone. At this time, virtually everyone under the age of 45 used a computer and even the age group 45 – 65 years old adapted computers at this point. In addition, almost everyone below the age of 34 was using a smartphone in 2016. This phenomenon of younger people adopting technology faster is also part of research in the communications and education sciences with Prensky (2001) coining the term digital native for those who have been growing up with digital technologies all their lives[7].

[7] Some more papers and indeed books on digital natives and their influence include Correa (2014), Nelissen (2018) and Palfrey and Gasser (2011). Kirschner and De Bruyckere (2017) offer a more critical perspective.

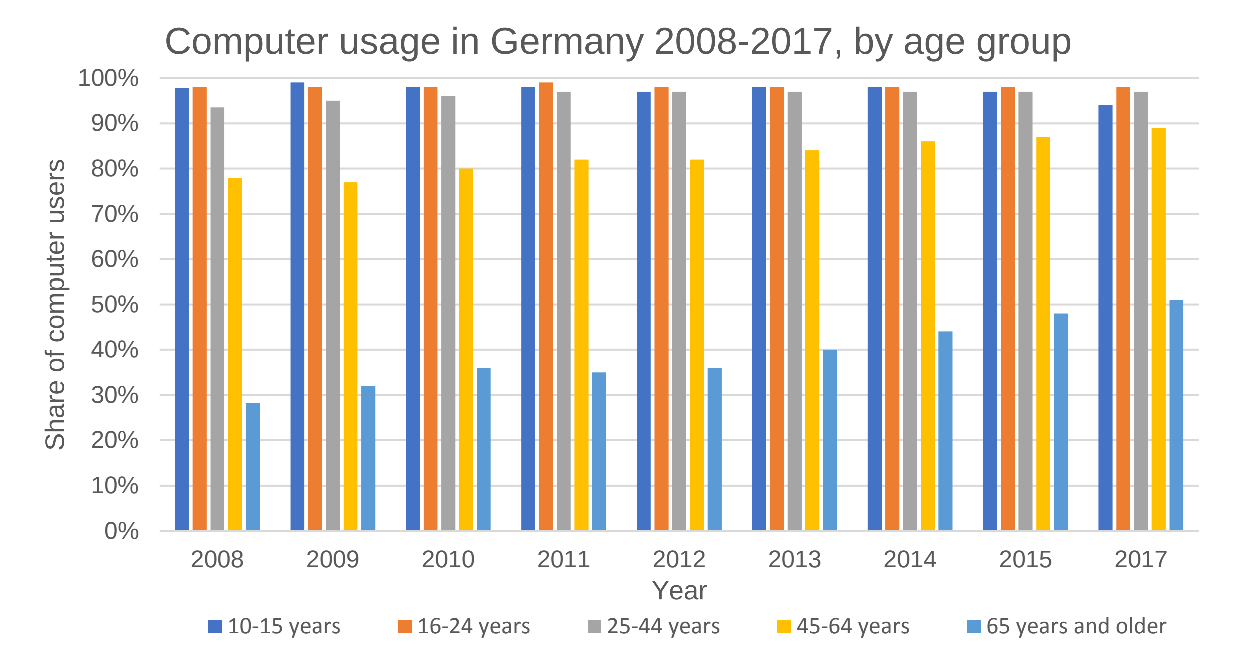

Figure 4: *Computer usage in Germany 2008-2017, by age group*

Note: Computer usage in Germany 2008-2017, by age groups 10-15, 16-24, 25-44, 45-64 and 65 years and older according to Statistisches Bundesamt (2017).

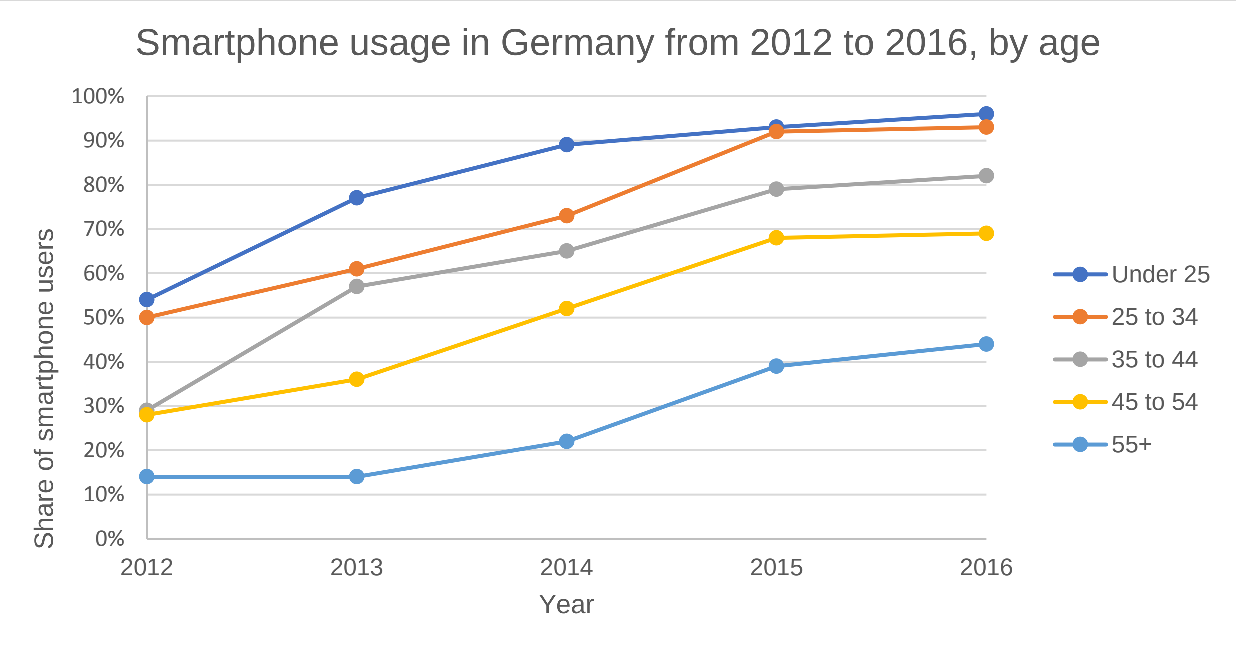

Figure 5: *Smartphone usage in Germany from 2012 to 2016, by age*

Note: Smartphone usage in Germany 2012-2016, by age groups under 25, 25-34, 35-44,45-54 and 55 years and older according to Google and TNS Infratest (2018).

Figure 4 and *Figure 5* not only show that younger people are more intensively using new technologies, but they also show that the older people are, the harder it generally is to adapt to new technologies. Of course, it is not difficult to imagine the tremendous amount of technological change a person remembering a world with black and white television and households with no telephone connection has witnessed. When looking at the world today, where everyone has an internet connected devise in their pocket, having to relearn the different stages of technology like using a smartphone can be tiring[8]. The further technology advances, the further the world changes from the environment one grew up in and the more new things have to be learned to stay up to date. This is not to say that there are no children in our societies that cannot perfectly use technology as well as that there are no older people that are enthusiastically noticing new technological trends. However, a general case can be made for an increasing difficulty in adaptation to new technologies with age. In a way, the world changes more and more from what one was taught, and relearning becomes less and less intuitive or maybe even wanted. In some cases, the usefulness of new technology is not readily apparent to older people and they stop adopting new pieces of technology or are very slow in their adoption.

Alas, as alluded to before, technological change does not only affect everyday life, but it also changes the way people work. Businesses now use computers and the internet while many production facilities are highly automated. Older workers have lived with and adapted to the changes new technology has brought to their workplaces. Yet, the amount of change experienced by each person is different, especially when looking at technological change in the workplace. The way a carpenter does his business and the skill required to do so may not have changed as profoundly as for example the way a doctor, stockbroker or a secretary are doing their work. In the workplace, it is the occupation one is pursuing more than anything, which determines whether the impact of technological change on the work was high or low, rather than the general speed of technological innovation and the individual age. Thus, the amount a worker must adapt to technological change is dependent on three things: their occupation, the speed of technological change in each period and the length of time this person has spent working.

[8] Anderson and Perrin (2017) and Ma et al (2016) talk about technology use of older people while Hong et al (2016), McGaughey et al (2013) and Rosales et al (2016) examine smartphone use of older people.

This amount of technological change a worker must adapt to is referred to as **technological age** and forms the basis of this analysis. Technological age is thought to make workers skills obsolete and can be understood like human capital depreciation induced by experienced technological change. If it becomes more difficult to adapt to new technologies the more technological change a person has witnessed, the difficulty to adapt should be reflected in the working environment. This thesis therefore measures technological age on an individual level and uses technological age to test whether people who have lived through more technological change in their occupations receive a lower wage due to their technological age or decide to leave their occupation more frequently. The analysis thus covers both, the impact of technological age on wages and the impact of technological age when leaving an occupation. After discussing the relevant literature, placing this work into the relevant scientific context and motivating this topic further in Section *2*, Section *3* introduces the concept of technological age in more detail. After showing a short theoretical interpretation of technological age, the regression functions for the analysis of the impact of technological age and the decision to change occupations are shown in Section *4*. Then in Section *5*, after discussing a measure of technological change, the data that the analysis is based on is introduced. Finally, the wage and occupation change analyses are reported in Sections *6* through *9*. Their results are further compared and discussed in Sections *10* and *11 Discussion* in order to come to a general conclusion of the impact of technological age in Section *12*.

In more detail, Section *2, Literature,* shortly discusses general technological change literature[9]. Then, the literature discussing the impact of technological change on older workers skills is split into three strands: the first strand looking at computer usage of older workers, the second strand looking at computer usage and retirement decisions of older workers and the third strand, analyzing the labor demand of innovative firms with regards to older workers.

The first strand looking at computer usage of older workers[10] is inconclusive as some find a negative relationship between age and computer usage and some find

[9] Such as Acemoglu (2002), Acemoglu and Autor (2011), Antonczyk, DeLeire, and Fitzenberger (2018), Autor and Dorn (2013), Dustmann, Ludsteck, and Schönberg (2009), Fitzenberger and Kohn (2006), Spitz-Oener (2006), Tüzemen and Willis (2013) and Van Reenen (2011).

[10] Including Bertschek and Meyer (2009), Borghans and Ter Weel (2002), Czaja and Sharit (1993), de Koning and Gelderblom (2006), Friedberg (2003), Morris and Venkatesh (2000), Meyer (2011) and Schleife (2006).

none. The second strand, looking at computer usage and retirement decision of older workers[11] finds a general positive relationship between technological change and early retirement. The final strand of literature analyzes the labor demand of (innovative) firms of older workers[12], showing that innovative firms have a lower demand for older workers. However, this literature only looks at older workers but ignores the individually experienced technological change and its impact. The amount of technological change each older worker must adapt to is different as technological change is different for each age group and occupation. Furthermore, the literature only looks at select (innovative) industries or treats all occupations the same. This thesis remedies these shortcomings. Both individually experienced technological change as well as an occupation specific analysis form the basis of this analysis.

Following Section *2*, Section *3* explains the concept of technological age in more detail. As technological age is a novel concept, it is important to be understood as it forms the underlying idea of the thesis. The concept of technological age is then in turn used to define the research questions more clearly.

Next, Section *4, Applied Models,* further explains the concept of technological age and the way it influences wages with a short formal model. From this model, the regression functions for the wage analysis and the occupation change analysis are derived and explained in more detail.

Section *5* then explains the data used in the analysis. In order to measure technological change, this thesis uses data from the "Employment Survey of the Working Population on Qualification and Working conditions in Germany" of the Bundesinstitut für Berufsbildung, ("BIBB") which is called *"BIBB Data"* in this analysis. This dataset is a detailed telephone survey completed in five waves from 1979 until 2006[13]. Each wave includes questions on the use of computers and similar occupation classifications. This information is used to map average computer usage in each occupation over time and will serve as a measure of technological change. This lays the foundation for an occupation specific technological change measure.

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[11] Including Ahituv and Zeira (2011), and Bartel and Sicherman (1993).

[12] This includes Abowd et. al. (2007), Aubert, Caroli and Roger (2006), Beckmann (2007), Behaghel, Caroli, and Roger (2014) and Schleife (2008).

[13] A sixth wave exists; however, it uses a different occupation classification and is only utilized for robustness checks.

The occupation specific technological change information is then added to the dataset “Sample of integrated labor market biographies”, of the “Institut für Arbeitsmarkt und Berufsforschung”, which from here on is called *“SIAB Data”*. This dataset encompasses a two percent random draw of the social security paying German workers in the timeframe 1975-2014. It gives individual wage and employment information as well further personal characteristics such as age and education. Since the occupation classification is the same in both datasets, it is possible to map technological age for each individual in the dataset on the basis of time employed per occupation. The combined data on occupation specific technological age stemming from the *BIBB Data* survey and the data individual earnings and employment biographies from the *SIAB Data* form the basis for the wage and occupation change analysis.

Section *6, Wage analysis,* reports the results of the wage analysis. First, a regression across the entire timeframe of 1979-2006 is reported and discussed. The negative impact of technological age on wages is clearly visible; however, it does not entirely influence all occupations in the same way. Moreover, in some occupations there is a positive impact of technological age on wages. Since the linear regression assumes a constant impact of technological age across the sample period, the timeframe is split into three subsamples, 1979-1989, 1990-1999 and 2000-2006. The three timeframes are called “*subsample 79*”, “*subsample 90*” and “*subsample 00”* from now on, while the sample period of 1979-2006 is called “*overall sample”*. The subsample periods illuminate whether the impact of technological age differs across time. Generally, technological age had a more positive impact on wages in *subsample 79* and *subsample 90*, while in *subsample 00* wages in all occupations were negatively affected by technological age. After reporting and discussing the results of the subsample regressions, robustness checks using a different occupation classification and extending the sample period are reported and discussed.

In Section *8, Occupation change analysis,* the results of the occupation change analysis are reported in a similar fashion to the wage analysis. First, the regression results for the *overall sample* are reported. Then the sample is split into the three subsample timeframes of *subsample 79, subsample 90 and subsample 00*. Similar to the wage analysis, the results for the *overall sample* make it clear that technological age has an impact on the likelihood to leave an occupation. In most occupations, technological age makes workers more likely to leave their occupations. Alas, in some occupation technological age makes workers more likely to stay. The trend for the split sample periods in the occupation change analysis is contrary to the trend of the wage analysis. In *subsample 79* and *subsample 90* workers are much more likely to leave their occupations due to technological age for almost all occupations, while in *subsample 00* workers are less likely to leave due to technological age. After discussing the results, robustness checks similar to the wage analysis are performed for the occupation change analysis.

Furthermore, the thesis looks at similarities and differences of the impact of technological age on wages and occupation change in Section *10*. Generally, technological age had a more negative impact on wages *subsample 00,* while technological age made workers more likely to leave their occupations in *subsample 79* and *subsample 90*. Finally, Section *11* discusses possible problems of the analysis and the need for further research before Section *12* concludes the thesis.

2 Literature

Technological change has been on researchers' minds since the late 1990's and early 2000's. As such, a vast literature on technological change exists. In the early 2000's and before, many influential papers like Acemoglu (2002)[14] argued for the existence of skill biased technological change. Card and DiNardo (2002) and others[15] questioned this finding, which led to the rise of the literature of wage polarization due to technological change. Among others[16], Acemoglu and Autor (2011), and Autor and Dorn (2013) argue for a more task-based approach[17]. Technological advances lead to a substitution of routine tasks while highly complex-non routine tasks are being complemented by technological change. This in turn leads to a large depression of the wages of middle-income workers, while high-income workers receive a wage premium according to Tüzemen and Willis (2013). Thus, the general impact of technological change on wages is thought to be well understood.

The literature regarding the interplay of age and technological change can be divided into three strands. The first strand looks at the computer use of older workers. The second strand explores the relationship between technological change and early retirement and the third strand analyzes the demand of older workers by (innovative) firms and older workers wage bill share. In this context, more innovative firms seem to favor younger employees.

In more detail, the first strand looking at the computer use of older workers comes to differing conclusions. Borghans and Ter Weel (2002) find no impact of age on the computer usage of older workers in the UK but find that older workers are less skilled at using computers. Looking at Germany, Schleife (2006) finds a strongly negative relationship between age and computer usage, while Bertschek and Meyer (2009) find that older workers compared to younger workers are not less productive when working

14 Acemoglu (2003), Katz, Autor (1999), Krueger (1993), Monte (2011) and Lemieux (2006)

15 For example, Autor (2014), Lemieux (2006), Mazzolari, F. and Guiseppe (2013), Reshef, A (2013), and Spitz-Oener (2006) also paint a more complicated picture.

16 Autor and Handel (2013), Autor and Murnane (2003), Van Reenen (2011) also analyzes wage polarization but further draws connections to trade influencing technological change. Antonczyk, DeLeire, and Fitzenberger (2018), Biewen and Seckler (2017), Card, Heining and Kline (2013) and Dustmann, Ludsteck, Schönberg (2009) for example, provide an analysis for Germany.

17 Fitzenberger and Kohn (2006) extend this to cohorts and employment, Hershbein and Kahn (2017) argue that the great recession accelerated this trend, Acemoglu and Restrepo (2017) look at automation, age and economic growth.

with computers. In the Netherlands, de Koning and Gelderblom (2006) find a negative relationship between age and computer usage while Czaja and Sharit (1993) analyze that older workers make more mistakes when using a computer. Morris and Venkatesh (2000) show that there are differences in technology usage decisions between older and younger workers, with older workers being influenced by perceived behavior control and subjective norms. Meyer (2011) takes a different viewpoint and finds that firms with a younger workforce are more likely to adopt new technology compared to firms with an older workforce. Finally, Friedberg (2003), using US data, finds a negative relationship between computer usage and age only for the very old workers and links this to an investment decision into new skills when workers get close to retirement. The very old might not want to invest into new skills, (i.e., computer skills), if they cannot reap the payoffs of their investment. Overall, this strand of literature does not allow drawing general conclusions concerning the computer usage of older workers. While some parts of the literature find a negative relationship between age and computer usage, others find none at all.

The thought process of Friedberg (2003) above, linking technological change and retirement decisions already gave a preview of the second strand of literature. These authors look at the use of computers and retirement decisions of older workers. Friedberg poses her arguments (older workers not wanting to train due to the loss of return on investment of training) similar to Bartel and Sicherman (1993) who approach the issue using another perspective. Bartel and Sicherman conclude that if workers receive training, they are less likely to retire early. However, this does not hold if there is an unexpected technological shock. In that case, people are more likely to retire early regardless of their training. Additionally, Ahituv and Zeira (2011) also find a positive relationship between early retirement, old age unemployment and technological change. Generally, technological change happening pushed workers into early retirement as their skills become obsolete. The more unexpected technological change occurs, the more pronounced this effect seems to be.

The final strand of literature analyzes the labor demand of (innovative) firms for older workers. Generally, innovative firms seem to show a higher demand for younger workers. Both Aubert, Caroli and Roger (2006) and Beckmann (2007) show that innovative firms, i.e., firms using new technologies, have a lower demand for older workers when looking at the wage bill share of older workers[18]. However, Rønningen (2007) only finds this true for workers in their fifties when compared to workers in their forties while the younger and older workers are unaffected. Abowd et. al. (2007) show that firms using advanced technologies are more likely to hire high ability workers but less likely to hire high experience workers. Schleife (2008) also comes to the result that innovative firms have a lower demand for older workers yet points out that training can lessen this effect and lead to higher participation of older workers. Similarly, Behaghel, Caroli, and Roger (2014) show that the negative employment prospects of older workers is weakened by training (at least to a degree). Overall, innovative firms rely more strongly on younger workers, even though this effect might be offset by training.

In conclusion, there is some evidence that older workers are probably less likely to use computers or that when older workers use computers they are often not as proficient in their use. However, this evidence is not conclusive. In addition, technological change pushes older workers into earlier retirements and makes (especially innovative) firms less likely to hire older workers. While the first strand of literature regarding computer use of older workers is inconclusive, the second strand of literature is clear in suggesting that technological change can make workers skills obsolete and thus pushes them into early retirement. Furthermore, more innovative firms seem to value younger workers more and using a larger part of their wage bill share for younger workers as presented in the third strand.

Alas, there are some major shortcomings of the existing literature, which this thesis attempts to remedy. First, most existing literature does not necessarily consider how much technological change a worker has experienced over the course of his or her lifetime. It is also unclear if the amount of technological change experienced is crucial when trying to determine the impact of technological change on older workers. Generally, available analyses only look at older versus younger workers, ignoring the amount of individual technological change experienced. Additionally, the fact that the influence of technological change on the loss of human capital might be considerably different in different occupations is not discussed in detail. Either innovative firms are the basis for the analysis, limiting the kind of occupations present or a general view is

[18] As a side note, Cardoso, Guimarães and Varejão (2011) show that older workers might be underpaid as their productivity contribution exceeds their part of the wage bill share.

taken, treating all occupations in the same way. Yet clearly, these simplifications could potentially make or break the results of the analyses. A person experiencing a lot of technological change in occupation A might be impacted completely differently by technological change than a person working in occupation B. Furthermore, the amount of technological change differs tremendously between occupations so that many nuances of the impact of technological change on workers might be lost when assuming all occupations to behave the same way.

This thesis attempts to remedy both, the shortcoming of ignoring individually experienced technological change and the shortcoming of ignoring occupation specific differences when it comes to the impact of technological change. In order to do so, this analysis uses the concept of technological age to describe the amount of technological change a single person has experienced over his or her (working) lifetime. This individual measure of human capital depreciation due to experienced technological change forms the basis of an occupation specific analysis. The thesis shows the negative impact of technological age in most occupations while similarly illustrating that technological age increases the likelihood of workers leaving most occupations. Furthermore, the difference in occupational impact is be made clear alongside the fact that the effects of wage and occupation change appear at different times. The next section further explains the concept of technological age and motivates the research objectives in more detail.

3 The concept of technological age

While the term technological age has already been alluded to in this thesis, the concept of technological age is not only novel in research but also integral to understanding the following analysis. The first important assumption is that children generally grow up with the newest technology available. Communications and education sciences use the term digital native to describe this phenomenon[19], while data describing the use of computers or smartphones also points in this direction. Younger people are much more likely to use new technology compared to older people and the older a person becomes, the less likely he/she is to use new technology. Furthermore, the time it takes for older people to adopt new technologies increases with age. The reasoning behind the assumption that children generally grow up with the newest technology available is thus simple[20].

The second assumption is that the more technological change a person has witnessed, the less likely this person is to easily adapt to new technologies. For each cohort, their childhood is normal and the available technology levels are natural. Furthermore, the costs of investing into learning new technologies might outweigh the returns at some point in people's lives, in turn with Friedberg (2003), Bartel and Sicherman (1993) and Ahituv and Zeira (2011) mentioned in Section *2*. In a broader sense, the idea that returns to investment into human capital development must at least cover the costs of said human capital development is also discussed by Card (1999), Heckmann et. al. (2008) and Heckmann et. al. (2006) among others.

For each cohort, technological innovations only become something new when one gets older. Thus, when people start working, they are aware of the newest technologies and they are likely using the newest technology themselves already. The more technology changes and the older workers become, the less likely they are to use new technologies themselves in their free time. Furthermore, the more technology changes, the more each person must adapt and acquire new knowledge, as their old knowledge is outdated. Additionally, the more technology changes, the more it differs from the

[19] The term digital natives is coined by Prensky (2001). As given in the Section *1 Introduction*, more papers and on digital natives and their influence include Correa (2014), Nelissen (2018) and Palfrey and Gasser (2011). Kirschner and De Bruyckere (2017) offer a more critical perspective.
[20] For reference here again the digital native's literature given in the *Introduction*: Correa (2014), Nelissen (2018) and Palfrey and Gasser (2011). Kirschner and De Bruyckere (2017) offer a more critical perspective.

level of technological knowledge the person has started with. If then a worker has experienced a lot of technological change in their occupation during their time working, things differ further from the way work was done when they started. This difference requires a larger investment in learning new technologies when compared to an occupation with little or no technological change. All of these aspects make it more difficult to adapt to new technologies, the more technological change one person has experienced.

While now the key assumptions are that children grow up with the newest technology levels and more technological change makes it more difficult for older workers to adapt, technological change does not affect all older workers in the same way. Three aspects are deciding the amount of technological change a person has experienced in the workplace and now must adapt to and thus are the building blocks of technological age:

1. The occupation a worker is employed in
2. The speed of technological advances during the timeframe the worker was working
3. The length of the timeframe a worker has spent working

Of course, occupations have large differences in their technological intensity as well as in the speed they have to adapt to technology. Workers in the IT occupation have an obvious mandate to keep up with and stay on top of new technological advances. This might be true to a lesser extent for administrative occupations, where technological change will affect the work eventually, but where new technologies are not necessarily implemented immediately. In contrast, workers in the construction occupations might have to adapt to technologies even later.

The speed of technological advances naturally differs in different timeframes. While in the last years technology has changed rapidly and has subsequently influenced everyday life, there have been periods in history where technology changed much slower. Thus, the technological advances during the timeframe a worker was working has a paramount impact. Lastly, it is obvious that a person working for a long time in an occupation prone to be susceptible to technological change and during a timeframe with a lot of technological change has experienced more technological change than a person who has only worked for a short while in the same occupation.

In order to illustrate this point further, one might consider a farmer or a smith in medieval times. While there were continuous technological advances even then, their speed was so slow that many sons taking up their fathers' trade might go about this trade in much the same way their fathers and indeed even their grandfathers before them had. The work of a farmer or a smith stayed very similar for years and years[21]. The same could be said for example for housekeepers during the industrial revolution. While their tools might have slightly changed, the general nature of the work remained the same. Not so, for example for weavers during this period, who saw the nature of their work change to the core with the introduction of steam powered weaving looms[22]. Not only did the tools change but also the entire nature of the workplace evolved.

The amount of technological change a person has experienced in their working life is therefore called their technological age. It is thus an interplay of the occupation a person is pursuing, the time a person is pursuing this occupation in and the difference in technology between the time this person started working up to the present day. Overall, one could see the concept of technological age as technological specific human capital depreciation[23]. Each young worker enters with a high amount of technologically specific human capital acquired naturally when growing up. When technological change happens, this human capital depreciates more and more, depending on the occupation, the speed of technological change in each occupation and the time spent working in each occupation. The more technological change a person has experienced in their occupation, the larger the depreciation of the human capital should be. Of course, measures such as training might mitigate the depreciation effect, yet the bigger the difference between starting technology level and current technology level in the occupation, the harder it should be to adapt.

Technological age is therefore a measure of the individual, technology specific human capital depreciation. Technological age increases when technology changes during a person's working life. The more technological change a worker has experienced, the higher the worker's technological age. Compared to age, technological age is thus not a measure of how much time has passed since a persons' birth but rather

[21] While the paper by Epstein (1998) is largely about the impact of guilds in the middle ages, it still covers technological change at the time.
[22] Goldin and Katz (1998) write about technological change and its impact early in the 20th century.
[23] More on the depreciation of human capital: example Arrazola and Hevia (2004), Arrazola et al (2005), Bapna et al (2013), Hanushek et. al. (2017), Kunze, (2002) McFadden (2008), Mincer and Ofek (1982) and Weber (2014).

how much technology has changed since a persons' entry into the labor market. A person might have worked in an occupation with little or no technological change for a long time and thus accruing no technological age while another might be working in a technologically quickly changing occupation, accruing a large amount of technological age in a short time. Workers with a large technological age should have a harder time adapting to new technology in their occupation and should in turn be less efficient when working with or learning new technology than compared to workers with a lower technological age. This leads to the first hypothesis.

First Hypothesis:

Technological age makes workers less efficient when using new technologies.

If Hypothesis 1 holds, meaning if technological change depreciates a person's technological human capital and the person becomes less and less efficient in learning new technologies and using these new technologies, the question becomes in which ways does this manifest and how does this loss of efficiency affect workers. The first thing coming to mind reflecting the efficiency of a worker in the labor market is their wage. The less efficient a worker, the less money he/she should earn according to basic economic thought. While in the short run, wage might not be flexible and a wage reflecting a worker's efficiency might not be paid, in the long run wages should reflect a loss in working efficiency. The first option thus is that a worker with more technological age should earn less wages when compared to a worker with less technological age, ceteris paribus. It is important, that this comparative wage deficit does not have to mean that a person with more technological age would receive a total wage decrease. In fact, a technologically old workers' wage might increase over time due to the increase in experience or seniority pay. The wage effect of technological age might also manifest itself in the form of less raises or promotion opportunities due to technological age. Therefore, if the first hypothesis holds, the second hypothesis should also be true.

Second Hypothesis:

Technological age decreases workers' wages.

Another possibility how technological age and the increased inefficiency when using new technologies could affect workers rather than being paid less money is that a worker might simply decide to change occupations. When changing into an occupation where technology has changed less compared to when he/she started, this worker's technological age would be reduced. If the new occupation has seen less technological change than the old one, the level of technology should be closer to the starting technology of the worker and the worker should be more efficient again. Further reasons to change occupations due to technological change are that a worker might not feel comfortable in his or her occupation anymore and that he/she feels like they are left behind. Workers could feel like they cannot catch up anymore, perform their task well, and therefore change their occupation leading to the third hypothesis.

Third Hypothesis:

Technological age makes workers more likely to change occupations.

By showing the negative impact of technological age on wages and by showing the impact of technological age when it comes to workers' likelihood to leave occupations, not only are Hypotheses 2 & 3 proven for most occupations in this analysis, Hypothesis 1 is also likely to be true as Hypotheses 2 & 3 build on Hypothesis 1.

Technological age is thus an individual measure of technological human capital depreciation. Technological age is accrued occupation specific and can have an occupation specific impact. The more technological age one worker has accrued, the more inefficient he/she should become at handling new technologies. This inefficiency can manifest itself in the wages of a worker or in the decision of a worker to leave his/her occupation. The next section formalizes the concept of technological age with a short theoretical model. From this model, the regression models for the wage analysis and the occupation change analysis are derived.

4 Applied Models

4.1 Theoretical model of technological age

While the general concept of technological age has been explained and the underlying thought of human capital depreciation is not overly complicated, this thesis gives a simple theoretical model formally explaining the thought process behind the concept of technological age[24]. The model is held purposefully basic, and the goal is not to form a general equilibrium but rather to highlight the concept of technological age formally and show how it should influence workers' wages. Furthermore, this model takes into account the three points forming the basis of technological age: The occupation a worker is employed in, the speed of technological advances during the timeframe the worker was working and the length of the timeframe a worker has spent working. In addition, this model is the basis for the regression functions used later on in the analysis. Following, the model is introduced building the basis for the regression models explained in the next sections.

The model first starts with a simple Cobb-Douglas production function of an occupation j in time period t. This thesis assumes $K = 1$ for simplicity's sake.

$$Y_{jt} = A_{jt} {L_{jt}}^{\alpha_j} \tag{1}$$

The labor supply in Equation *(1)* is provided by individuals working in occupation j at time t. The most interesting aspect is that each individual providing labor is also part of a cohort τ. The cohort of an individual never changes as the cohort describes the individuals' entry time into the labor force. This thesis assumes that knowledge of technology is greatest when entering the labor force; the cohort builds the foundation for discerning technological age. The difference of technology between the point in time τ, i.e. the entry into the labor force, and the point in time t gives the technological

[24] This model has been developed and refined in collaboration with Philipp Harms, Professor at the Johannes Gutenberg-University, Mainz.

age of a person. The labor supply of an individual i from cohort τ, working in occupation j at time t is given by:

(2) $$L_{\tau jt}^{i} = \frac{\delta_{it} L (A_{j\tau})^{\theta_j}}{A_{jt}}$$

The labor supply of an individual in occupation j at time t is dependent on their personal characteristics δ_{it}. It increases with the technology in occupation j at the time of entry into the labor force $A_{j\tau}$ and decreases with the technology in occupation j at time t, described with the term A_{jt}. Furthermore, there is a term θ_j that describes the impact of the starting technology $A_{j\tau}$ on the labor supply. Finally, L simply describes effective labor units. The variables affecting the individuals labor supply is explained in more detail below.

The variable capturing personal characteristics, δ_{it} describes things such as age, gender, education and time spent unemployed. The difference between starting technology $A_{j\tau}$ and the technology at point t, A_{jt}, gives the basis for technological age. The starting technology $A_{j\tau}$ can of course never change. Even after changing occupation, the occupation specific starting technology remains the same. The impact of technological age on labor supplied is moderated by θ_j. θ_j is ≥ 0 and allows for occupation specific impact of technological change on labor supply. Thus, in some occupations technological age impacts labor supply extremely while in others the impact might be minimal. The point of differing technological impact per occupation (θ_j) cannot be stressed enough. It is in no way assumed that technological change has a similar impact on comparable workers in different occupations but rather that the impact can differ from occupation to occupation, allowing for occupation specific technological impact.

When adding up the labor supply of all individuals in occupation j at time t one gets the total labor supply, which is given by:

(3) $$L_{jt} = \sum_{\tau=\tau_0}^{t} \sum_{i=1}^{N_\tau} L_{\tau jt}^{i}$$

The total labor supply is simply the sum of all individual labor supplied starting with the labor from the oldest working cohort τ_0 to the newest cohort still working at $\tau = t$.

The optimal wage of an individual is thus given by:

$$(4) \qquad w_{jt}^{*} = \alpha_j A_{jt} \left(\sum_{\tau=\tau_0}^{t} \sum_{i=1}^{N_\tau} L_{\tau jt}^{i} \right)^{\alpha_j - 1}$$

The optimal wage w_{jt}^{*} increases with current technology level A_{jt} but decreases with the total amount of labor supplied across all cohorts in occupation j. Plugging in Equation *(2)* and Equation *(4)* into the standard income function, leads to the income of an individual:

$$(5) \qquad I_{\tau jt}^{i} = w_{jt}^{*} L_{\tau jt}^{i} = \alpha_j \left(\frac{A_{jt}}{\sum_{\tau=\tau_0}^{t} \sum_{i=1}^{N_\tau} \delta_{it} L(A_{j\tau})^{\theta_j}} \right)^{1-\alpha_j} \delta_{it} L(A_{j\tau})^{\theta_j}$$

Equation *(5)*, while giving the income of an individual, is by itself not offering very much information. However, when comparing the income of two individuals from different cohorts τ, Equation *(5)* provides necessary information. Dividing the income of an individual from cohort τ given by Equation *(5)* by the income of an individual k from cohort τ', which is also given by Equation *(5)* when changing the individual and cohort accordingly, the comparison is very simple. The large term in the parenthesis simply capturing the technology in occupation j at time t and the total labor supply in occupation j, showing that income increases with technology but decreases with total labor supplied, as well as the α_j simply cancel out as they are the same for both individuals. Equation *(6)* then depicts the income differences:

$$(6) \qquad \frac{I_{\tau jt}^{i}}{I_{\tau' jt}^{k}} = \frac{\delta_{it}}{\delta_{kt}} \frac{(A_{j\tau})^{\theta_j}}{(A_{j\tau'})^{\theta_j}}$$

Equation *(6)* shows that apart from the personal characteristics δ_{it} and δ_{kt}, the reason for receiving a different income is a different starting point in technology when entering the labor force. Another way to look at this difference is that one individual enters the labor force at point τ in time. The next individual joins the labor force later, at point τ'. Since the technological progression is the same for both individuals after point τ', the difference in their technological age is the difference between $A_{j\tau}$ and $A_{j\tau'}$. As alluded to above, θ_j describes the occupation specific impact of the starting technology and allows for differing impact of technological age in different occupations. The same numerical difference in technological age could have differing impacts on the income of individuals in different occupations. As this thesis is looking for the impact of technological age on wages and on changing occupations, the goal of the regression analysis is to estimate the impact of technological age θ_j for each occupation.

Following, the regression function for the wage analysis, based on this short model, is depicted and explained. Then, the regression function for the occupation change analysis is depicted and explained.

4.2 Regression model wage analysis

As stated in the last section, the main goal of the empirical analysis is to derive θ_j for each occupation j, explaining the occupation specific impact of technological age on wage per occupation. The following regression function is derived from the above model[25] and is estimated as a log-log, person fixed effects model. The reasoning behind using a log-log model is in one part due to the derivation from the model as well as providing the interplay between technological age and wages the possibility to behave nonlinear. The model in Section *4.1* predicts each level of technological age to have an influence on each individual's wages. Yet as the dataset used is an unbalanced panel dataset[26], the regression analysis utilizes a person fixed effects model. This leads to the analysis only taking into account the effect of change in technological

[25] Further information can be found in Appendix *A1.*
[26] More information on the data can be found in Section *5.2.1 Data description SIAB Data.*

age on the change in wages. As there are 28 occupations, a total of 28 occupation specific θ_j are estimated. The regression function is as follows:

$$(7)\quad lnI_{ij\tau t} = \beta_0 + \theta_j\{[ln(1 + A_{jt}) - ln(1 + A_{j\tau})] * occupation_{ijt}\} + \beta_1 \ln \delta_{it} + \beta_2 vocTrain_{it} + \beta_{3j} occupation_{ijt} + \beta_4 state_{it} + \beta_5 Ind_{it} + \beta_{6t} * d_{it} + \varepsilon_{ij\tau t}$$

Generally, the variables used in the regression approach are the same as used in the formal model described in Equations *(1)* through *(6)*. $ln\, I^i_{\tau t}$ is the log daily wage of an individual i at time t from cohort τ, working in occupation j. θ_j is the occupational effect of technological age on wages, $A_{j\tau}$ is the starting technology of cohort τ in occupation j and A_{jt} is the technology in occupation j at point t. δ_{it} describes the personal characteristics consisting of a comprehensive set of measured characteristics. δ_{it} includes a log age variable, a log employment complexity variable describing the required skill level for the position held in the company, a variable capturing the amount of log former jobs a person has had, a variable capturing the days a person has spent unemployed, a log experience variable (capturing the amount of years spent in the current occupation) and a variable capturing employment change in occupation j. $vocTrain_{it}$ is a vocational training dummy with 4 different occupation levels. ind_{it} is an industry dummy as most occupations can be practiced in many different industries and $state_{it}$ is a state dummy. Finally, d_{it} is a time dummy. More insight into how the variables are conceived in the data and how they measure their information is given in Section *5.2.2 Created variables SIAB Data*.

Following, the term $\theta_j\left[ln(1 + A_{jt}) - ln(1 + A_{j\tau})\right]$ is explained in more detail, as it is the centerpiece for estimating the impact of technological age on wages. First, the cohort τ is explained, followed by the starting technology $A_{j\tau}$ and finally finishing with the whole term.

The entry point in the labor market τ

τ represents the starting cohort for each worker. It is assumed that every worker enters the labor market at the age 17, determining τ for every worker. This entry point is set somewhat arbitrarily but the reasoning for this decision is that the lowest age found in the *SIAB Data* dataset is 17. It furthermore seems like a fair working starting age as people not pursuing a college education and starting to work immediately after high school[27] should predominantly be about 17 years old. While for people going to study at university, their entry into the labor force is delayed longer by their studies, this is only a small share of the population in the sample. It could also be fair to assume, that university students do not keep up with the newest technology as they did in school. Further possibilities of a bias could come from unobserved education such as training on the job or other informal training, which could be captured by this variable. Overall, setting the starting technology age at the age of 17 might lead to some individually overestimated technological ages, yet estimating a too large technological age due to an earlier labor force entry should only weaken the effect of technological age found.

The starting technology $A_{j\tau}$

As alluded to in the model description, the starting technology of $A_{j\tau}$ is assumed to be constant. If a person changed to an occupation where ten percent of workers used a computer at point τ from an occupation that used no computer at all at point τ, the starting technology $A_{j\tau}$ of said person would be zero. The reasoning for keeping $A_{j\tau}$ constant through occupational changes is that a person's past knowledge of technology cannot change in the present. In more detail, the underlying thought process for keeping the starting technology constant is that when a person switches occupation at some point in his or her working lifetime, the knowledge of technology that this person had at point τ cannot change later in their lifetime. If a person started working in a low technology occupation and subsequently had no idea about utilizing technology in the beginning of his or her career τ, it is impossible for him/her to switch to an occupation that extensively used computers at point τ and now suddenly have known about

[27] According to *Table A20: Observations and levels of the "Vocational Training" variable* in Appendix *A7,* this statement is true for 91.13 percent of observations.

using computers all along. Not keeping the starting technology $A_{j\tau}$ constant could lead to some other absurd cases where a person started working in an occupation that made a lot of use of computers at his/her entry into the labor force, point τ. Then, later in life, when switching to an occupation that made no use of computers at point τ, he or she would have to suddenly loose all past knowledge and not have known anything about using computers at point τ. Alas, a person can naturally not lose knowledge he or she had in the past due to switching occupation in the present. Another reason for keeping the starting technology $A_{j\tau}$ constant is the German vocational training system. There might be some amount of occupation specific training a person receives when entering the labor market further cementing his or her starting technological knowledge for the occupation he or she started working in[28]. Since the underlying intuition behind technological age is that people understand the technology they start with and due to technological change lose that innate understanding of technology more and more, keeping the original $A_{j\tau}$ constant across occupation changes is the only sensible option.

The technological age term $\boldsymbol{\theta_j}[\boldsymbol{ln}(\mathbf{1}+\boldsymbol{A_{jt}})-\boldsymbol{ln}(\mathbf{1}+\boldsymbol{A_{j\tau}})]$

The term $[ln(1+A_{jt})-ln(1+A_{j\tau})]$ subtracts the starting technology $\boldsymbol{A_{j\tau}}$ from the current technology $\boldsymbol{A_{jt}}$. In a more technical way, the term $\left[ln(1+A_{jt})-ln(1+A_{j\tau})\right]$ is the log of the average technology of occupation j at point t minus the log of the average technology of occupation *j* at point τ. This difference is interacted with a dummy variable from occupation *j*. As this term is interacted with occupation dummies, it gives the log impact of technological age on log wage per occupation.

$\left[ln(1+A_{jt})-ln(1+A_{j\tau})\right]$ is also a term that is increasing in technological age. This means that the larger this term is, the more technological change a person has experienced and the higher is the technological age of a person. Of course, the impact of log technological age in log wages is given by θ_j. Alas, measuring technological age is not trivial. A is proxied by the percent of workers who used a computer in occupation j at points t and τ, a deeper discussion into the measurement of technology is given in Section *5.1.1*. The reason for adding one to $A_{j\tau}$ and A_{jt} in the regression function,

[28] Hanushek et al. (2017) also point in this direction with their finding that vocational training further lessens the adaptability when it comes to new technologies later in the working lifecycle.

Equation *(7)*, is that many occupations had no computer users at all at the beginning of the analysis (as can be seen in the technology overview in *Figure 6* to *Figure 9* in Section *5.1.4*). Since taking the natural log of computer users in occupations where average computer usage was zero percent is impossible, a one was added to all values making it possible to take the log of computer users in all occupations. As adding one to the computer usage percentages does not change the logs of the technological ages much, this should not have a large impact on the results. Naturally, by adding one to all of the computer usage numbers, the analysis would infer that what matters is the level difference between technological age and a starting technology being zero does not actually have a special effect. Furthermore, the person fixed effects regression only looks at the within variation for each person anyways and a special effect for not using technology at all would not be estimated either way.

Ideally, the regression function would be estimated for each occupation separately, making it possible for the personal characteristics δ_{it} and the dummies to have an occupation specific effect on wages. Alas estimating the regression for each individual occupation separately leads to several problems. First, occupations changes and estimations considering workers occupation changes are no longer possible as the workers changing occupations would not be present in the regression for occupation j anymore. Yet, even more importantly, the amount of change in technology per occupation is the same for every observation in a given year due to the way technological change is measured. Thus, a time dummy would not be possible for a regression with only one occupation, as the technological change would be collinear to the time dummies. Leaving out the time dummies leads to further problems as time fixed effects would no longer be included and time specific shocks might be measured as the impact of technological age. Using a polynomial time trend is also not helpful as the time dummies have to capture one-time effects like the German reunification[29]. One could of course attempt to estimate all controls for each occupation within one regression using interaction terms. Yet, the number of occupations and personal characteristics would lead to 1204 interaction terms and estimated variables. Furthermore,

[29] More details to special circumstances in the data can be found in Section *5.2.1*.

an occupation specific time fixed effect would not be possible either, as explained above.

Therefore, the regression is estimated for all occupations simultaneously, using an interaction term to estimate θ_j for each j and non-occupation specific personal characteristics and dummies. The regression furthermore omits the main effect for technological age and only estimates the effect of technological age interacted with the occupation dummy. Conventionally, when using an interaction term, both parts of the interaction are by themselves present in the regression also. In this case, the regression would include a term for technological age, an occupation dummy and the interaction between the two. The downside of including both, the terms for technological age and the occupation dummies, as well as the interaction in the regression is that the regression provides an effect for each of the non-interacted parts and one for the interaction. Here, the regression would provide an effect for each occupation dummy, a general effect of technological age and an effect of technological age in each occupation. Alas, the analysis is interested in the full effect of technological age per occupation. Omitting the overall effect of technological age from the regression, the effect of the interaction term of the occupation dummy and technological age provides the full effect of technological age for each of the occupations. Simply put, the result for the θ_j is similar to running a single regression for each occupation.

In summary, the regression function, Equation *(7),* utilizes a log-log, person fixed effects approach directly derived from the theoretical model and omits the main effect for technological age in order to estimate the full effect of log technological per occupation for all occupations at the same time. While this regression model forms the basis for the wage analysis, the next section explains the regression model for the occupation change analysis.

4.3 Regression model occupation change analysis

The influence of technological age on wages is not the only way technological age could affect workers as mentioned in Section *3*. Another possibility is that workers leave their occupation due to technological age. This section gives insight into the regression model used to estimate the effect of technological age on changing occupations.

Since the nature of the dataset is the same as for the wage analysis, meaning both are utilizing an unbalanced panel set, the occupation change analysis also utilizes a person fixed effects model where the effect of technological age on changing occupations is estimated for each occupation. Both regression models are closely related for comparability, they measure technological age in the same way and have the same control variables. Considering the panel nature of the data, it is possible to see when workers change occupations. This fact is used to create a fixed effects linear probability model, with the dependent variable being one if the worker changes their occupation in the next period and is zero otherwise. The advantage is that it is possible to see the influence of technological age on the decision to leave an occupation in the future. The impact of technological age on the likelihood to leave an occupation in the next period is thus estimated by:

$$(8)\ occ\_change\_future_{ij\tau t} = \beta_0 + \theta_j\{[A_{jt} - A_{j\tau}] * occupation_{ijt}\} + \beta_1 \ln \delta_{it} + \beta_2 vocTrain_{it} + \beta_{3j} occupation_{ijt} + \beta_4 state_{it} + \beta_5 Ind_{it} + \beta_{6t} * d_{it} + \varepsilon_{ij\tau t}$$

The reason for not using a logit or probit approach while dealing with a binary dependent variable is that in order to take the panel nature of the data into account and to estimate comparable results to the wage regressions, a fixed effects approach is necessary. As a fixed effects logit regression makes it impossible to estimate average partial effects as well as partial effects on the response probabilities[30], this thesis

[30] Wooldridge (2010), pp. 490 ff.

employs a fixed effects linear probability model making interpretation of the partial effects and comparison with the wage results possible.

The dependent variable $occ\_change\_future_{ij\tau t}$ is coded in a way that it is one if an individual changes occupation in the next period and zero otherwise. The focus on the occupation change in the next period is important if the goal is to find whether technological age pushed people to change their occupations. Similar to Equation *(7),* the wage regression, an individual probability is estimated for each occupation. Thus, a causal relationship between occupation specific individual technological age and leaving one's occupation can be established. The disadvantage with this approach is that it is impossible to see where the workers change occupations to and whether they decrease their technological age in doing so. However, if it is possible to show that technological age makes workers more likely to change occupations and which occupations are more likely to have employees leave due to technological age, some parallels to the wage regression might be established. It can be possible to say whether the workers in occupations already being paid less due to technological age are also leaving their occupations and thus showing an even greater negative impact of technological age on these occupations, or whether workers in occupations that are not experiencing a negative wage effect due to technological age are leaving their occupation regardless.

Of course, another big difference of the wage regression function, Equation *(7)* compared to the occupation change regression function, Equation *(8)*, is that the occupation change regression function does not use logs. When looking at the theoretical model, it makes sense to use logs in the wage regression. Alas, in a regression with a binary dependent variable it makes little sense to keep using logs, as it is not possible to depict an elasticity anymore. Thus, the occupation change regression function does not utilize logs but rather includes the same independent variables as the wage regression, simply without logs. All the other variables are exactly the same as described in Section *4.2*, technological age is also coded in the same way. Adding one to all of the computer usage percentages is not necessary, as without logs there is no more reason to add one to every technological age score. The only difference in terms of explanatory variables when comparing the wage regression function Equation *(7)* and the occupation change regression function Equation *(8)* is the addition of an age-squared variable. The nature of the year fixed effects makes it impossible to include an age variable without introducing multicollinearity. Yet it is paramount to separate the effect of age from the effect of technological age, thus a nonlinear age measure should be included. As it is common practice to include age squared (or some form of age non-linearity) into the regression, age squared is chosen in this case[31].

Something to keep in mind is that as there can be no technological change data for unemployed workers as unemployment is not an occupation where measuring computer use is possible. Alas, workers can change their occupation to another occupation, or they can become unemployed. When looking at job changing behavior, it is thus paramount not to forget about unemployment. The occupation change regression is estimated once without accounting for unemployment, simply looking at whether workers change to a different occupation due to technological age. After that, as a robustness check, the occupation change regression is estimated once more including the occupation change into unemployment.

Summarizing, the occupation change regression Equation *(8)* utilizes a person fixed effects linear probability model to estimate the likelihood of a person leaving their occupation in the next time period *t*. The further aspects of the model, such as explanatory variables and the measurement of technological age are the same as in the wage regression function Equation *(7)*. The next section discusses measuring technological change and points out the difficulties involved before moving on to describe the data.

[31] The addition of the age squared variable does not change much. Not only is the variable insignificant, leaving age squared out of the regression does not impact the results much as evident in *Table A68* in Appendix *A15.vi*.

5 Data description

This thesis uses two datasets, the “Employment Survey of the Working Population on Qualification and Working conditions in Germany” henceforth called *“BIBB Data”* and the Sample of integrated labor market biographies” from now on called *“SIAB Data”*. The *BIBB Data* is used to provide occupation specific computer use data, which is added to the *SIAB Data* in order to calculate a personal technological age. Therefore, Section *5.1* discusses the measurement of technological change alongside with the *BIBB Data* and the subsequent technological change numbers per occupation. Afterwards, Section *5.2* describes the *SIAB Data* and the process of using the *BIBB Data* to calculate technological age.

5.1 Extrapolating technological change using *BIBB Data*

5.1.1 Measuring technological change

In order to measure technological age adequately and in order to be able to assign a personal and occupation specific technological age to each person, one must correctly measure technological change first. As there exists such a large literature[32] on the impact of technological change, one might think this task trivial, yet this is far from true. While many papers talk about technological change and use a measure for technological change, there is some debate about how to measure technology and technological change correctly. There are several papers discussing this problem and many ways to measure technology[33]. The most popular measures include patents of company, patent filings of company, citations of company patents, R&D intensity, computer usage and many more.

One thing the literature largely agrees on is that each measure has distinctive shortcomings and is faulty when measuring technology on its own. Alas, it is often also

[32] The Literature on technological change is discussed in Section *2 Literature*.
[33] A few interesting papers talking about different measure of technological change: Archibugi, Planta (1996), Coccia (2005), Coombs and Bierly (2006) and Felsenstein, Bar-El, (1989).

not easy to gather the necessary data in order to have a more varied and holistic measure of technology. As many economics' papers use some measure of computer usage[34] to measure technology, this paper follows this approach. For its shortcomings, most prominently the fact that other forms of technology are not measured and that there can be many nuances in the complexity of computer usage, using computer usage to measure technology also has many positives. For one, it is easy to ask employees about computer usage and there is data readily available. Secondly, while computer usage does not measure the most innovative firms as R&D expenditure does and as computer usage does not for example keep in mind use of technologically intensive machinery, it is applicable for many occupations as a lot of occupations might not have R&D expenditures, much less patents. Furthermore, it shows a general form of technology that is used in many (if not most occupations) today and has changed many occupations profoundly. As general human capital depreciation through technological age is the premise for this thesis, computer usage is a good measure. By looking at computer usage in occupations over time, one can generally show a widespread technology adoption in each occupation. While one always has to keep this measures shortcoming in mind, computer usage is well equipped to map technological change over many occupations.

This thesis uses the *BIBB Data* from here on. It comes in five waves (for robustness checks a sixth wave is added) and gives detailed information about the working conditions in the timeframe from 1979 to 2006. This dataset is used to map technological change on an occupational level in the timeframe between 1979-2006 using the two-digit "Klassifikation der Berufe 88" (Classification of Occupations 88) which will be referred to by the official abbreviation, *"KldB88"*. A further introduction of the dataset, explanatory statistics and a mapping of technological change per occupation follows in the next sections. For the analysis, the occupations specific technological change measure is added to *SIAB Data* in order to create a measure of individual technological age, described in Section *5.2*.

[34] Papers that use computers are for example Autor, Katz and Krueger (1998), Card and DiNardo (2002) and Spitz-Oener (2006).

5.1.2 Data description *BIBB Data*

The information regarding occupational computer usage is provided by the *BIBB Data.* This dataset consists of five waves of telephone interviews in the timeframe from 1979 to 2006[35]. During the interview, participants were asked a wide array of questions regarding their working conditions. Even though the timeframe is quite long, and the questionnaire differs strongly over time, each wave offers a question about computer usage. Each wave also uses the *KldB88*, which makes it possible to discern the average computer usage per occupation per two-digit *KldB88*. For simplicity's sake, this thesis assumes a linear change of computer usage between each of the waves. Thus, it is possible to map computer usage per occupation over the timeframe from 1979 to 2006. This computer usage change is added into the *SIAB Data* in order to create a personal technological age.

Following, the five survey waves are listed in more detail with the dates and number of observations given and finally the exact questions asked regarding computer usage are discussed. The *KldB88* is explained in more detail, which occupations it entails and what those occupations are. Furthermore, more reasoning why the newer occupation classification "Klassifikation der Berufe 2010", called *"KldB2010"* is not used instead of the older *KldB88* is given.

Since the first wave in 1979 was still the time before rapid computerization (as can be seen in the data), this dataset is quite different form the data one is used to today as it was collected manually and only later digitalized. First, a survey had to be conducted and answered and the percentage of people owning a telephone in 1979 probably led some degree of sample selection bias. Second, the fact that this is a long survey (later waves claim that the interview takes about 45 min for their surveys) might lead some participants to interrupt and leave the interview. Furthermore, the 1979 and 1986 waves are only interviewing workers from West Germany, whereas East Germany appears from waves 1992 onwards. As the nature of questions of interest changed over time, the questions asked during the survey also changed substantially over the years. This can be seen by the number of variables used in each wave (see *Table 1* below) as well as the questions regarding computer usage themselves. The

[35] For more information about the Employment Survey of the Working Population on Qualification and Working conditions in German dataset, see Hall, Siefer, Tiemann (2014).

most comparable question regarding computer use from each wave of surveys was chosen, yet it must be clear that the questions are not exactly the same and thus might capture different nuances in their different iterations.

The following *Table 1 g*ives an overview over the dates of the waves, the exact number of observations and variables[36]:

Table 1: *BiBB Data waves, years, individuals interviewed and included number of variables*

Wave	Year	Individuals	Variables
1	1979	28,516	444
2	1986	26,186	190
3	1992	34,045	319
4	1999	34,020	789
5	2006	20,904	932
6 (only used for robustness)	2012	20,036	628

The exact questions per wave[37] are shown in *Table 2*:

Table 2: *The exact wording of the question asking about computer usage per wave of BIBB Data*

Wave	Year	Question Wording
1	1979	"In case the questioned is working: Following, tools machines and technical equipment are listed. Which do you use mainly? Please indicate the relevant equipment (by checking the right numbers)" Question V110 (Equipment number 52) is Computer, electronic data processing system, terminal, screen, with the options to check the box or not.
2	1986	Computer usage is split into different categories as part of the same question with different options to answer. "On the left, work equipment and machines are listed. There are means of transportation and cars as well as equipment for manufacturing and repairs. On the right, equipment for office, sales and others are listed. I would like to ask you, which do you use regularly during your work?" Question V88 gives the option to check Computer, electronic data processing system, screen or process computer. Question V108 gives the option to check personal computer. Question V109 gives the option to check computer, electronic data processing system. Question V110

[36] Some observations had to be excluded, as they did not feature a valid *KldB88* measure.
[37] Some questions are translated by me, as there are no English versions of the older surveys.

Wave	Year	Question Wording
		gives the option to check terminal, screen. If a person has answered yes to any of the above questions, he or she is counted as using computers in his/her work.
3	1992	Computer usage is split into different categories as part of the same question with different options to answer. “On this list there are equipment and machines. On the left, there are means of transportation and cars as well as equipment for manufacturing and repairs. On the right, equipment for office, sales and others are listed. Program controlled machines and computers are listed separately. I would like to ask you, which do you use regularly during your work?” Question V140 gives the option computer, terminal. Question V160 gives the option personal computer, question V161 the option electronic data processing system, question V162 the option terminal, screen. As above, if a person has answered yes to any of the above questions, he or she is counted as using computers in his/her work.
4	1999	Computer usage is split into different categories as part of the same question with different options to answer. “(In case you are working with computers and data processing tools [Question V53 had to be answered with yes]) When you look at the below list, which (computer or data processing tolls) are those? Please tell me the corresponding number.” Question V54 gives to option to name personal, office computer, question V55 the option to name computer, electronic data processing system with access to an internal network, question V56 the options to name computer, electronic data processing system with access to an external network and question V57 the option to name laptops or notebooks.
5	2006	“Would you please tell me how frequent these tasks appear in your job?” Question f318 asks working with computers. The answering options are often sometimes, never and no answer. If a person answered sometimes or often, he/she was set to have used computers.

In order to measure technological change per occupation and the impact of technological age per occupation, one has to define occupation classifications as well. This thesis utilizes the *KldB88* occupation classification. According to the “Statistische Ämter des Bundes und der Länder, Klassifikationsserver[38]” (2011), “The Classification of Occupations or *KldB* provides a basis for showing the occupational situation in Germany in a realistic way and to present the occupational structure in statistics and analysis adequately. The Classification of Occupations in its version of 1988 (KldB88) is based on the occupation classification of 1970. This version was updated in 1975, to a large extent keeping the structure up to the three-digit level (Berufsordnungen)...”

[38] Official translation: Classification Server of the Statistical offices of the Federation and the Länder

Thus, the *KldB88* is a German classification of occupations. It assigns a four-digit code to each occupation. Each digit of code further breaks down the occupation into occupation areas and sections. The first digit orders the occupations into five occupational areas named below:

1. Farmers, Animal Breeding and Fishing
2. Miners, Mineral Exploitation
3. Production
4. Technical Occupations
5. Service Occupations

A sixth area called "others" exists but has no relevance to this analysis, as there is no data available.

The occupational areas are then split up into sections. Some areas have only one section such as the areas 1 and 2. Others have up to 19 sections such as the "production" area. This thesis uses a modified set of sections applied by the *SIAB Data*[39], listed below[40] in *Table 3: KldB88 section and variable names as used in SIAB Data by number*:

[39] Those are not the exact areas of the *KldB88* as the *SIAB Data* uses a different set of areas. More Information in Appendix *A2.*
[40] As this modified set of section of the *SIAB Data* merges some section of the original *KldB88*, the numbering further on also does not reflect the original section numbers.

Table 3: *KldB88 section and variable names as used in SIAB Data by number*

Number	Section	Variable name
1	Farmers, Animal Breeding, Fishing	agriculture_fishing
2	Miners, Mineral Exploitation, Stone Workers, Building Material Production	miners_stone_workers
3	Ceramic, Glas Production	ceramic_glas
4	Chemistry Workers, Synthetics Production	chemistry_synthetic_workers
5	Paper making and processing, Printing	paper_print
6	Wood Treating, Wooden Goods Production and Simi-lar	woodworking
7	Metal Making and Working	metal_works
8	Locksmith, Mechanics and Similar	mechanics
9	Electricians	electricians
10	Assembly and Other Metal Works	assembly
11	Textile and Clothing Occupations, Leather Production and Leather and Fur Processing	textile_clothing_leather_fur
12	Food Occupations	food
13	Construction	construction
14	Interior Construction, Upholsterer	interior_construction
15	Carpenters, Model Maker	carpenter
16	Painter, Varnisher and similar Occupations	painter
17	Product Tester, Shipment Preparation	product_testing
18	Machinist and similar Occupations	machinist
19	Engineers, Chemists, Physicists, Mathmaticians	engineer_math_chem

Number	Section	Variable name
20	Technicians, Technical Specialists	technical_specilaist
21	Goods Merchants	goods_merchants
22	Service Merchants and similar Occupations	service_merchants
23	Traffic Occupations	traffic
24	Organization, Administration and Office Occupations	administration
25	Regulatory and Safety Occupations	regulatory_safety
26	Writers, Artists	writing_art
27	Healthcare Occupations	healthcare
28	Social and Educational Occupations, other not mentioned Social Science and Science Occupations	social_education_science

As mentioned, this thesis uses the *KldB88* occupation classification, even though a newer version, the *KldB2010* occupation classification exists. The reason for using the *KldB88* in this analysis instead of the newer available *KldB2010* classification is mainly that the *KldB88* is the used classification in the data. Especially for the earlier waves, the *KldB2010* was not created yet. It is possible to transpose the older *KldB88* to the newer *KldB2010*, however, many occupations cannot be clearly transposed[41] leading to errors when classifying. The reasoning is that some occupations from the *KldB88* could be part of two or more classifications in the *KldB2010* (and vice versa). The waves 1979 to 2006 in *BIBB Data* use the *KldB88*, which eliminates having to transpose the data. Furthermore, the *SIAB Data* also has the *KldB88* classification implemented, making a comparison of the *KldB88* based occupation specific computer use from the *BIBB Data* much easier and less prone to errors than when having to try to transpose the classifications from *KldB88* to *KldB2010*.

[41] The transposition can be done according to the "Umsteigeschlüssel von der Klassifizierung der Berufe 1988 (4-Steller) zur Klassifikation der Berufe 2010 (5-Steller)" by the Bundesagentur für Arbeit (2011).

There are some downsides of using the *KldB88* instead of the *KldB2010*, the main one being the *KldB88's* extreme focus on manufacturing occupations, while giving a weaker division of especially more technical occupations[42]. Thus, this thesis employs the newer *KldB2010* as a robustness check. As explained, when using the *KldB2010*, all occupations in the waves 1979 to 2006 have to be transposed[43] from *KldB88* to *KldB2010*. However, an additional wave of *BIBB Data* (wave 2012) exists, using only the *KldB2010*, making robustness checks utilizing *KldB2010* possible for six further years. More information about the data with *KldB2010* can be found in Appendix *A5*.

Knowing the exact number of computer users in each occupation in each wave is used to calculate the average computer users per occupation and wave. This information leads to detailed computer usage averages for each occupation in 1979, 1986, 1992, 1999 and 2006. In order to have yearly average computer usage numbers, changes in computer usage between the waves were assumed to be linear for simplicity's sake. Using the computer usage information from the five waves, the assumed average computer usage per year was calculated, showing how many people on average used a computer each year from 1979 to 2006 in each of the *KldB88* classification levels. In the next step, some descriptive statistics of the *BIBB Data* are given before mapping the technological change per occupation.

[42] Matthes and Paulus (2013) give a detailed account on the difference between *KldB88* and *KldB2010* and why the *KldB88* had to be updated.
[43] The transpositions were done by me, using "Umsteigeschlüssel von der Klassifizierung der Berufe 1988 (4-Steller) zur Klassifikation der Berufe 2010 (5-Steller)." by the Bundesagentur für Arbeit (2011) transposition table.

5.1.3 Descriptive statistics *BIBB Data*

Considering the only information used from the *BIBB Data* is the number of observations across the occupations and the distribution of computer usage per occupation, those are the only descriptive statistics given. Thus, *Table 4* and *Table 5* depict the number of observations per occupation as well as their share of the total in percent. The first thing that becomes clear is that naturally the observations per occupation are very unevenly distributed. Especially metal_works (7) has very few observations with only fielding a total of four observations in the 2006 wave. In contrast, the number of observations for healthcare (27) reaches as high as 6,929 in the 1999 wave. Of course, a low number of observations could potentially lead to a false technology progression later on which is something to keep in mind. Yet, most of the occupations should have enough observations to infer a technology usage for the whole occupation.

Table 6 and *Table 7* show the number of people who do and who do not use a computer per occupation. The numbers of computer users are used for the calculation of which percentage of workers uses a computer in each occupation in a given point in time. As stated already, the progression of computer usage between waves is assumed to be linear and therefore the graphs of technological change shown in the next section are fully based on *Table A3* to *Table A6* in Appendix *A4*. Since it is much simpler to have an overview over the technological progression in graphical form, the depiction follows in the next section, Section *5.1.4*.

Table 4: *Number of observations per KldB88 and percentage of observations per KldB88 as part of total observations, wave 1979, 1986 and 1992*

		1979		1986		1992	
KldB88	Number	Freq.	Percent	Freq.	Percent	Freq.	Percent
agriculture_fishing	1	825	2.89	862	3.29	941	2.764
miners_stone_workers	2	173	0.61	79	0.30	96	0.282
ceramic_glas	4	74	0.26	61	0.23	80	0.235
chemistry_synthetic_workers	5	217	0.76	220	0.84	282	0.828
paper_print	6	252	0.88	252	0.96	242	0.711
woodworking	7	20	0.07	49	0.19	37	0.109
metal_works	8	526	1.84	436	1.67	688	2.021
mechanics	9	2,183	7.66	2,038	7.78	2,541	7.464
electricians	10	799	2.80	790	3.02	1,060	3.114
assembly	11	216	0.76	174	0.66	248	0.728
textile_clothing_leather_fur	12	576	2.02	354	1.35	381	1.119
food	14	624	2.19	550	2.10	770	2.262
construction	15	911	3.19	843	3.22	1,136	3.337
interior_construction	16	212	0.74	229	0.87	227	0.667
carpenter	17	342	1.20	315	1.20	394	1.157
painter	18	301	1.06	288	1.10	371	1.090
product_testing	19	268	0.94	231	0.88	381	1.119
machinist	21	350	1.23	245	0.94	560	1.645
engineer_math_chem	22	639	2.24	626	2.39	1,194	3.507
technical_specilaist	23	1,418	4.97	1,005	3.84	1,387	4.074
goods_merchants	24	2,632	9.23	2,374	9.07	2,946	8.653
service_merchants	25	973	3.41	1,201	4.59	1,183	3.475
traffic	26	1,781	6.25	1,542	5.89	2,170	6.374
administration	27	6,301	22.10	4,956	18.93	6,588	19.351
regulatory_safety	28	840	2.95	737	2.81	1,021	2.999
writing_art	29	289	1.01	395	1.51	473	1.389
healthcare	30	1,078	3.78	1,147	4.38	1,477	4.338
social_education_science	31	1,627	5.71	2,009	7.67	2,614	7.678
Total		28,516	100	26,186	100	34,045	100

Table 5: *Number of observations per KldB88 and percentage of observations per KldB88 as part of total observations, wave 1999 and 2006*

		1999		2006	
KldB88	Number	Freq.	Percent	Freq.	Percent
agriculture_fishing	1	732	2.15	359	1.80
miners_stone_workers	2	55	0.16	16	0.08
ceramic_glas	4	45	0.13	33	0.17
chemistry_synthetic_workers	5	207	0.61	139	0.70
paper_print	6	221	0.65	147	0.74
woodworking	7	33	0.10	4	0.02
metal_works	8	372	1.09	279	1.40
mechanics	9	2,172	6.38	979	4.92
electricians	10	843	2.48	403	2.02
assembly	11	157	0.46	159	0.80
textile_clothing_leather_fur	12	204	0.60	54	0.27
food	14	744	2.19	327	1.64
construction	15	1,101	3.24	264	1.33
interior_construction	16	307	0.90	107	0.54
carpenter	17	351	1.03	136	0.68
painter	18	289	0.85	101	0.51
product_testing	19	300	0.88	292	1.47
machinist	21	379	1.11	224	1.13
engineer_math_chem	22	995	2.92	795	3.99
technical_specilaist	23	1,321	3.88	779	3.91
goods_merchants	24	3,327	9.78	1,514	7.61
service_merchants	25	1,451	4.27	963	4.84
traffic	26	1,946	5.72	1,075	5.40
administration	27	6,929	20.37	4,721	23.72
regulatory_safety	28	1,138	3.35	727	3.65
writing_art	29	594	1.75	433	2.18
healthcare	30	1,971	5.79	1,453	7.30
social_education_science	31	3,237	9.51	2,441	12.26
Total		34,020	100	19,904	100

Table 6: *Number of observations per KldB88, who do and who do not use a computer, waves 1979, 1986 and 1992*

		1979		1986		1992	
		Computer usage		Computer usage		Computer usage	
KldB88	Number	No	Yes	No	Yes	No	Yes
agriculture_fishing	1	822	3	844	18	887	54
miners_stone_workers	2	170	3	110	2	128	8
ceramic_glas	4	74	0	61	0	77	3
chemistry_synthetic_workers	5	212	5	199	21	233	49
paper_print	6	235	17	219	33	174	68
woodworking	7	20	0	49	0	36	1
metal_works	8	525	1	427	9	631	57
mechanics	9	2,165	18	1,962	76	2,253	288
electricians	10	763	36	701	89	768	292
assembly	11	215	1	165	9	233	15
textile_clothing_leather_fur	12	574	2	439	7	463	12
food	14	622	2	544	6	743	27
construction	15	911	0	836	7	1,108	28
interior_construction	16	212	0	226	3	214	13
carpenter	17	342	0	311	4	363	31
painter	18	301	0	285	3	353	18
product_testing	19	265	3	217	14	311	70
machinist	21	346	4	230	15	511	49
engineer_math_chem	22	539	100	327	299	354	840
technical_specilaist	23	1,279	139	689	316	700	687
goods_merchants	24	2,553	79	2,045	329	2,277	669
service_merchants	25	784	189	566	635	273	910
traffic	26	1,740	41	1,462	80	1,942	228
administration	27	5,558	743	2,978	1,978	2,473	4,115
regulatory_safety	28	789	51	614	123	692	329
writing_art	29	280	9	315	80	278	195
healthcare	30	1,039	39	1,037	110	1,091	386
social_education_science	31	1,549	78	1,785	224	1,943	671
Total		26,943	1,573	21,671	4,515	23,802	10,243

Table 7: *Number of observations per KldB88, who do and who do not use a computer, wave 1999 and 2006*

		1999		2006	
		Computer usage		Computer usage	
KldB88	Number	No	Yes	No	Yes
agriculture_fishing	1	620	112	156	203
miners_stone_workers	2	82	6	19	20
ceramic_glas	4	36	9	17	16
chemistry_synthetic_workers	5	138	69	29	110
paper_print	6	139	82	32	115
woodworking	7	33	0	4	0
metal_works	8	331	41	78	201
mechanics	9	1,666	506	265	714
electricians	10	468	375	66	337
assembly	11	137	20	63	96
textile_clothing_leather_fur	12	224	16	38	29
food	14	677	67	204	123
construction	15	1,041	60	190	74
interior_construction	16	271	36	52	55
carpenter	17	292	59	58	78
painter	18	266	23	52	49
product_testing	19	220	80	87	205
machinist	21	313	66	60	164
engineer_math_chem	22	78	917	6	789
technical_specilaist	23	294	1,027	23	756
goods_merchants	24	1,919	1,408	364	1,150
service_merchants	25	93	1,358	11	952
traffic	26	1,588	358	462	613
administration	27	784	6,145	74	4,647
regulatory_safety	28	458	680	95	632
writing_art	29	202	392	37	396
healthcare	30	784	1,187	150	1,303
social_education_science	31	1,555	1,682	321	2,120
Total		16,962	17,058	3,632	16,272

5.1.4 Technological progression according to *BIBB Data*

Figure 6 to *Figure 9* show the computer usage development from 1979 to 2006 per occupation based on *Table A3* to *Table A6* in Appendix *A4*. Generally, each occupation starts out below 20 percent computer usage, most occupations start out below 10 percent. Then, different rates of computerization are evident and in 2006, most occupations still show a positive trend of computerization. The most technologically extreme occupations are engineer_math_chem (19), technical_specialists (20), service_merchants (22) and administration (24). All these occupations reached about 100 percent computer usage in 2006. On the other hand, construction (13) only reached about 28 percent computer usage while the most extreme, woodworking (6) is at 0 percent computer usage in 2006.

Overall, technology changes at different rates in the occupations with a generally expected trend towards more computerization being visible. The change in technology per occupation is used to create the technological age variable, mapping each person's technological age based on current occupation and entry into the labor force. As the change in technology form the basis for determining the technological age, it is important that there are definite occupation specific differences when it comes to technology adoption. The next section explains and describes the *SIAB Data*, into which these technology numbers are then added.

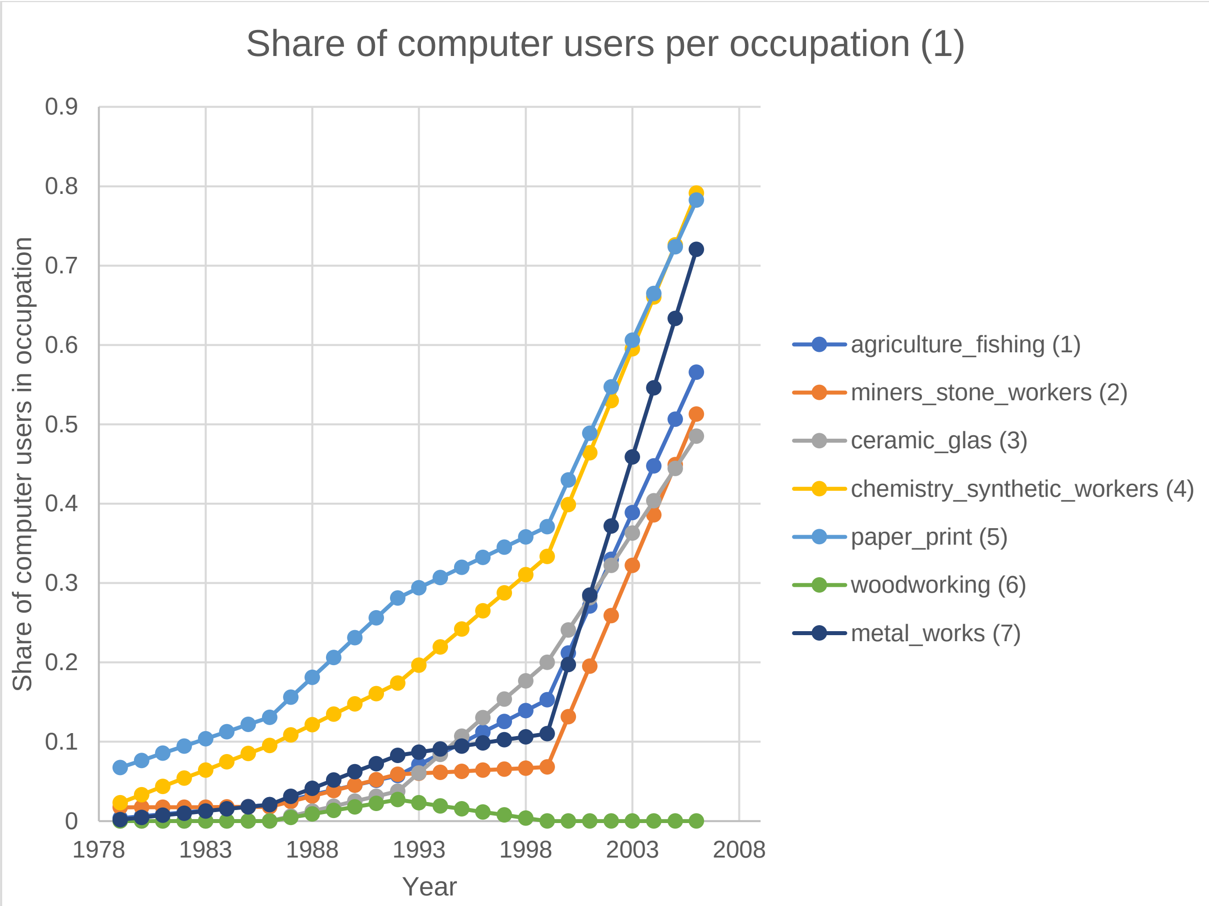

***Figure 6**: Share of computer users per occupation (1)*

Note: Yearly share of computer users for KldB88 1-7, based on Table A3 to *Table A6* in Appendix *A4.*

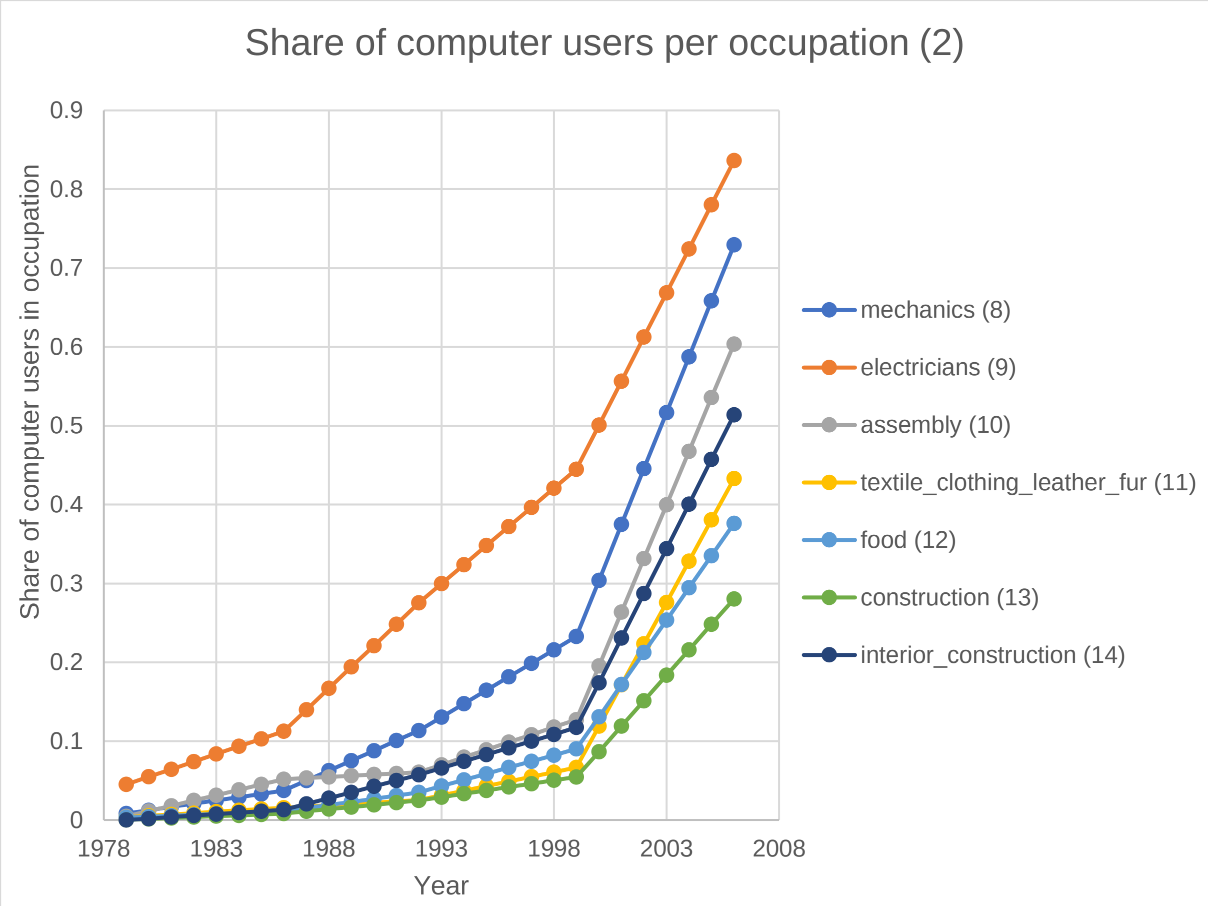

Figure 7: *Share of computer users per occupation (2)*

Note: Yearly share of computer users for KldB88 8-14, based on Table A3 to *Table A6* in Appendix *A4.*

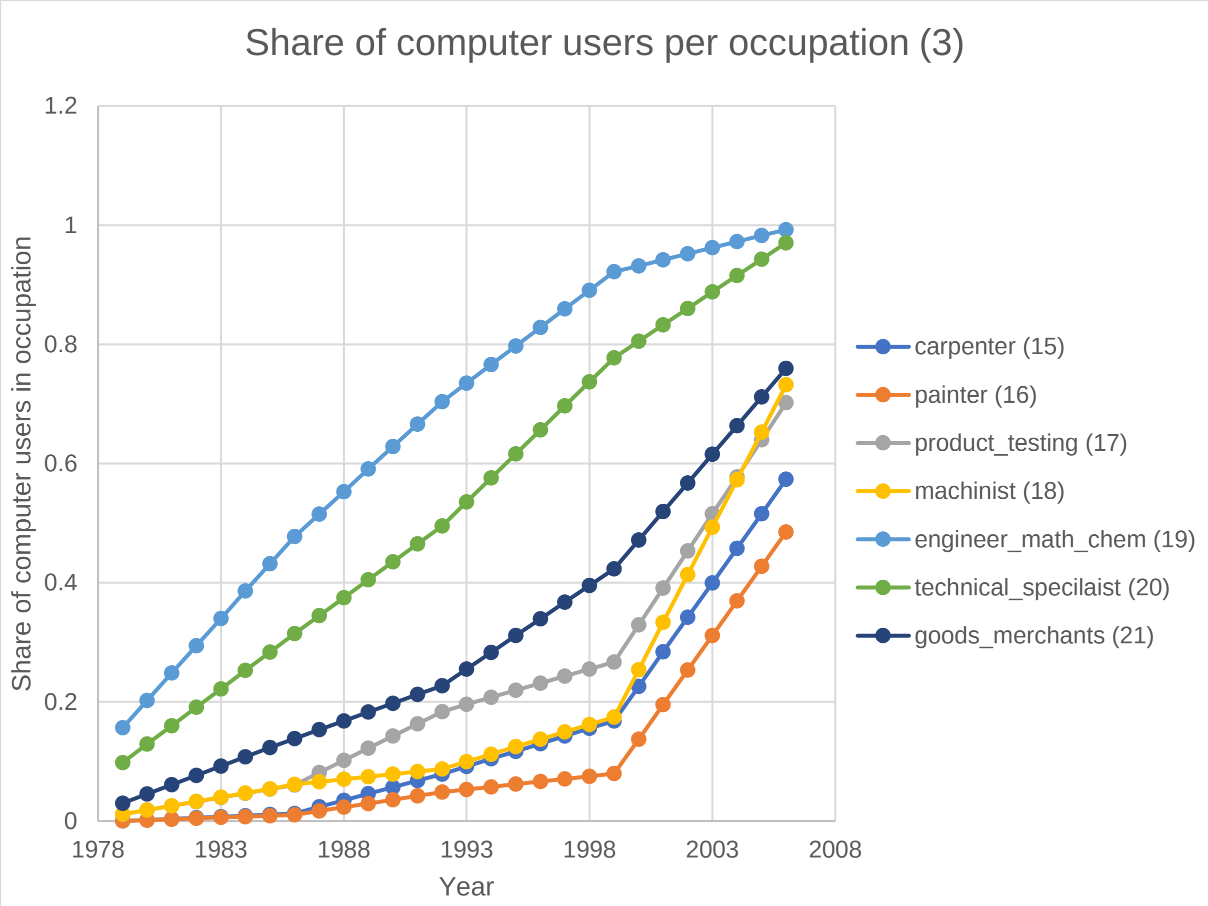

Figure 8: *Share of computer users per occupation (3)*

Note: Yearly share of computer users for KldB88 15-21, based on Table A3 to *Table A6* in Appendix *A4.*

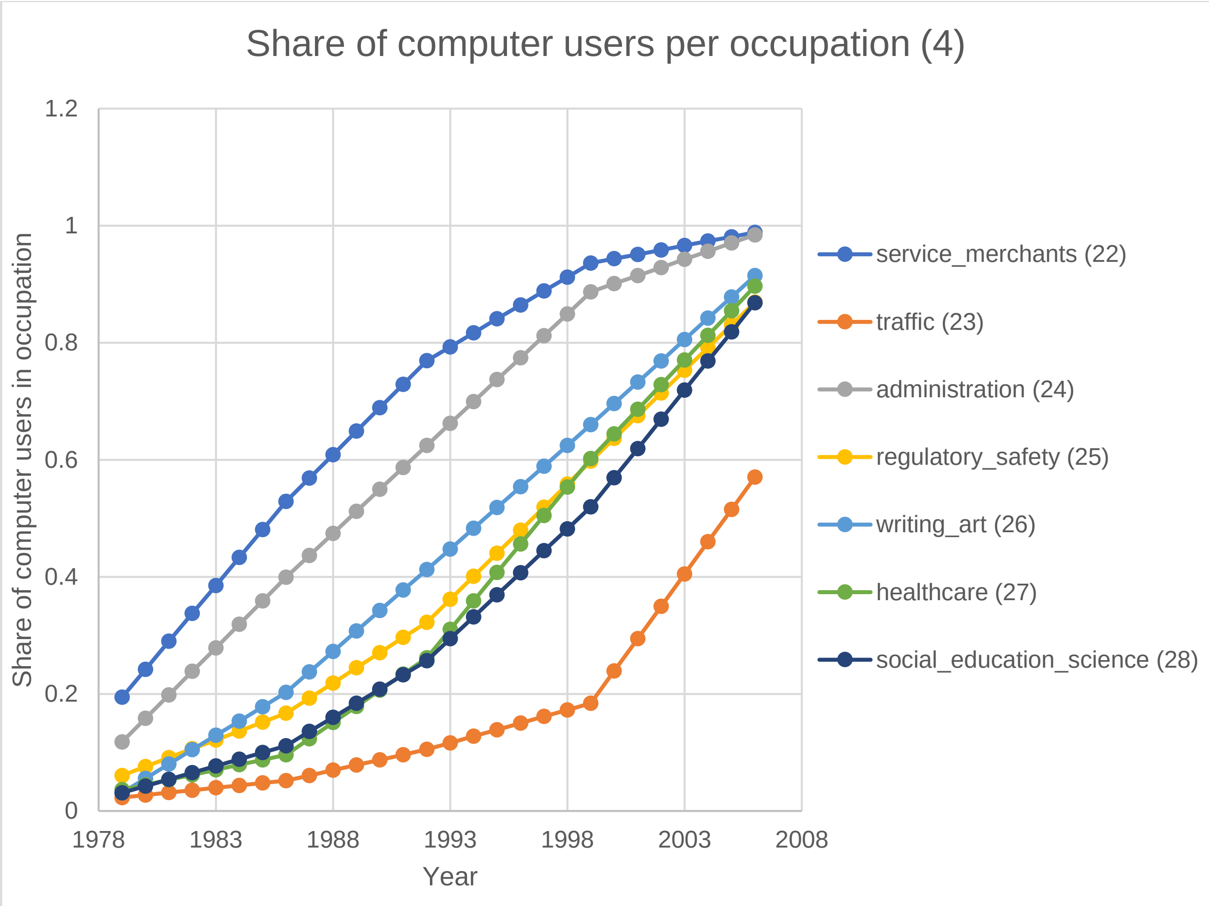

Figure 9: *Share of computer users per occupation (4)*

Note: Yearly share of computer users for KldB88 22-28, based on Table A3 to *Table A6* in Appendix *A4.*

5.2 *SIAB Data*

5.2.1 Data description *SIAB Data*

The dataset “Sample of integrated labor market biographies”, of the “Institut für Arbeitsmarkt und Berufsforschung” which is called *“SIAB Data”* in this thesis is the dataset into which the occupation specific computer usage numbers are added in order to create an individual technological age variable. This section gives a more detailed overview over the *SIAB Data* in general and the variables used in the analysis. The reasoning behind not using some observations from the *SIAB Data* is explained. Furthermore, some variables in the dataset have limitations, such as the top censoring of high wages. Established techniques to solve these issues are used to lessen the impact on the following analysis. Furthermore, the used variables in the analysis that were originally in the dataset are described as well as the newly created variables, most notably the working start variable and the following technological age variable. Finally, the slight differences for the data used in the occupation change analysis are explained.

The *SIAB Data* consists of a two percent random draw of the population of German employment biographies. The timeframe of the dataset encompasses the years 1975-2014. This means that anyone who was employed in an occupation subject to social security from 1975 onwards, or marginal, or part time employed from 1999 onwards, is part of the sample[44]. The actual sample is bigger still, yet it deals with unemployment data for which determination of technological age is impossible and thus is only used for robustness checks. Even though this is a large sample, one must keep in mind that occupations that are not subject to social security payments are not represented in the sample (such as government officials). Of course, this leads to some selection bias and does not allow for all occupations to be compared. However, the German social security system encompasses an overall extensive share of occupations, nonetheless. The dataset does not simply show a person at a single point in time but shows all the available employment data for each person between 1975-2014. This

[44] Ganzer, Andreas; Schmucker, Alexandra; vom Berge, Philipp; Wurdack, Anja (2016): Sample of Integrated Labour Market Biographies Regional File 1975-2014 (SIAB-R 7514). FDZ data report, 01/2017 (en), Nuremberg.

means that when a person changes from one occupation to the next or becomes unemployed, he/she is still part of the sample. The same is naturally true if a person works in a single occupation for many years. The *SIAB Data* uses this to build an earnings history of a drawn person showing all social security employment information. The *SIAB Data* is thus a large, unbalanced panel.

As explained in Section *4*, the regressions are estimated as a person fixed effects regression, which the panel lends itself to. Furthermore, in order to assign and track technological age for each person, one must know the occupations each person has worked in over time. The *SIAB Data* allows tracking the employment of individual people over time, making it possible to use the computer user data from the *BIBB Data* to calculate individual technological ages at every point in time.

While the *SIAB Data* starts in 1975 and ends in 2014, the earliest available wave of the *BIBB Data* is from 1979 and the latest (used) wave is from 2006. Thus, the years 1975-1978 and 2007-2014 are dropped[45] from the *SIAB Data*. The sub sample of the *SIAB Data* used for the analysis contains 11,012,285 observations from 971,510 individuals. In addition to dropping all observations before 1979 and after 2006, several other observations are dropped for various reasons in order to arrive at the final number of observations of 11,012,285. First, all part time workers and all persons not regularly employed are dropped. The reasoning behind this is that the dataset only reports daily wage, not monthly wage. People working part time can have large wages for the day but overall low monthly wages to the point where a part time worker could appear like an extraordinary earner. All persons not regularly employed such as interns, workers in training and job searching persons on the other hand earn much less (and in some cases nothing), skewing the wage observations for these occupations in the other direction making it necessary not to include them in the analysis.

The *SIAB Data*, contains a multitude of control variables. The dataset offers an easy way to create an approximate age variable as it contains the year of birth and year of observation for each observed worker. Of course, as discussed in Section *5.1.2*, *Data description BIBB Data*, the dataset contains a *KldB88* variable. It also contains a state variable (Bundesland) and an easy way to create a year variable, while

[45] As the *BIBB Data* has information of *KldB2010* in wave 6, the range of the analysis can be extended to 2012 for some robustness checks. Section *5.1.2* and Appendix *A5* give more information.

the original time variable is reported in days. The *SIAB Data* also provides an employment complexity measure consisting of four levels: assistant employment, professional employment, complex specialist employment and highly complex expert employment. There is a variable counting the number of former employers a worker has had as well as a variable counting the days a worker has spent unemployed. Additionally, the data offers vocational training and education variables and as mentioned above, a daily wage variable. Finally, the *SIAB Data* includes an industry variable which, based on the "Wirtschaftszweigklassifizierung 93" called *"W_93",* has thirteen different industries a worker can be employed in. A closer description of the *W_93* can be found in Appendix *A6*.

5.2.2 Created variables *SIAB Data*

Not all variables used in the regression were given, thus some still had to be created. First, workers working in an occupation for a long time might become more efficient due to their experience. As workers who have been working in the same occupation for a long time could also have accrued a large amount of technological age, it is crucial to control for experience in the regression. Since the dataset cannot offer an experience variable, this analysis created a variable counting the years spent in the same occupation while in the dataset. Obviously, it is impossible to count the experience of workers before they appear in the dataset but at least the experience the workers accrue while part of the dataset is accounted for. Naturally, this variable resumes the count when a worker has previously left the occupation but has now returned.

Furthermore, there are several observations that are missing the vocational training and education variable. Before those are dropped, an attempt to impute the missing observations from that data is made. This thesis closely follows the imputation procedure of the vocational training observations of Fitzenberger et. al. (2005). While this method might slightly overestimate the imputed education, other approaches probably underestimate the imputed education so that in the end it is a matter of personal preference which method to use. This thesis differs from Fitzenberger et. al. (2005) in one important way, namely that it combines the workers' university degree and technical college degree into one observation. The reason is that there are not many observations with a technical college degree to begin with (2.51% of all observations); even university and technical college combined still only amount to 8.87% of total observations. The final vocational training variable consists of five levels: No training, vocational training, high school, high school with vocational training and university.

The analysis also drops all observations when the daily wage is lower than one. The wage of zero usually alludes to people either being in maternity leave, in a sabbatical or in a similar situation where the employment relationship is continuing, yet no wage is paid. Thus, those people can increase their technological age but are also not earning any wages, skewing the analysis. The daily wage is given before taxes, yet until 1999, wages below the low-income threshold are not recorded (this threshold changes over time). In addition, there is a maximum amount to be paid for social security in Germany, which also increases over time. Income above this threshold is not recorded in the dataset but rather recorded as the highest amount of income that still has to pay the maximum amount for social security. The data is thus effectively top censored. The exact thresholds for low income and maximum social security payments are publicly available on the "Institut für Arbeitsmarkt und Berufsforschung" (IAB) website[46]. This thesis uses the method by Gärtner (2005) to impute the censored wages and to receive a more realistic wage variable in the data. This imputed wage variable is per definition already in a log form, fitting with the regression function in Section *4.2, Regression model wage analysis,* which is also working with logs.

Finally, while using year fixed effects in the regression accounts for countrywide shocks, shocks to the individual occupations cannot be captured. In order to be able to control for the occupation specific economic situation, this thesis uses a measure for how strongly employment has changed in each occupation compared to last year. As the measure had to fit perfectly with the *KldB88* grouping of the *SIAB Data*[47], employment numbers were taken from within the dataset. Obviously, this dataset does not encompass the whole German economy, yet it is a large sample of the German economy and as such should be able to adequately show trends between occupations. As there was a considerable increase in employment numbers after the German reunification, this analysis takes each occupations percentage share of total employment

[46] The IAB offers working tools including the income thresholds at https://fdz.iab.de/de/FDZ_Individual_Data/IAB_Employment_Samples/IAB_Employment_Samples_Working_Tools.aspx

[47] Section *5.1.2* mentions that the *SIAB Data* uses a different grouping of *KldB88* sections.

per year and calculates the differences in percentage points with regards to last year. This means that if agriculture had a two-percentage point increase in the total share of employment in the dataset between 1979 and 1980, the employment number for 1980 would be 0.02.

5.2.3 The technological age variable *SIAB Data*

The heart piece of the analysis is the measurement of technological age determined by $\boldsymbol{A_{j\tau}}$ and $\boldsymbol{A_{jt}}$**,** the technology in occupation *j* at point τ (entry into the labor force) and the technology in occupation *j* at point *t*. The technology in occupation j at points τ and t is given by the occupational computer usage number calculated in Section *5.1.4*. These occupational computer usage numbers are added into the *SIAB Data* and are used to calculate an individual technological age. In order to be able to determine the $\boldsymbol{A_{j\tau}}$, one first has to define a point of entry into the labor force. In this analysis, the point of entry into the labor force is set at 17 as this is the lowest working age in the *SIAB Data* [48] for regularly employed workers. For everyone who is of the age of 17 in the dataset, it is easy to set the starting technology $\boldsymbol{A_{j\tau}}$, since we know the occupation they are working in. It is more difficult for people who enter the dataset above the age of 17. Everyone above the age of 17 is assumed to have worked in their earliest shown occupation at the age of 17 and is given the starting technology from said occupation at the time they were 17 years old. Further difficulties lie in the people who were 17 before 1979, thus before the time the data on computer usage is recorded. All workers that entered the labor force before the computer usage data starts in 1979 are assumed to have the same starting technological age as workers starting in the same occupation in 1979. Naturally, this could be problematic, as the technological age is misestimated in some cases. However, the impact of this possible miss estimation is rather small for most occupations, as many occupations start with a computer usage of zero or close to zero in 1979. Furthermore, as the model being estimated is a person fixed effects model, it only takes within variation into account. As the yearly change in technology is unaffected by the starting technology of each worker, this sometimes-

[48] More reasoning behind this decision is given in Section *4.2*.

misestimated starting technological age should not be problematic. Alas, in order to make sure that the results are not impacted by misestimated starting technological ages, the issue of starting technology is addressed again in Sections 7.3 and 9.4.

The variable $\boldsymbol{A_{jt}}$, the technology in a certain occupation *j* at point in time *t* is simply added to the dataset using the *BIBB Data*. The technology in occupation *j* at the time of entry into the labor force τ and the technology in occupation *j* at point *t* form the basis of the technological age variable. The technological age variable is simply the difference between $\boldsymbol{A_{jt}}$ and $\boldsymbol{A_{j\tau}}$.

There are two possibilities of how $\boldsymbol{A_{jt} - A_{j\tau}}$ changes for each worker in each period. First, there is the yearly change in technology within each occupation. As the technology progression between the *BIBB Data* waves is linear[49], the change in technological age can be similar to the change in variation the year before, or whenever a new wave of technological change data exists, i.e., in the years 1986.1992 and 1999, the change in technological age is not similar to the period before. The second possibility of technological age change occurs whenever a person changes occupation. Due to the occupational nature of technological age, a change in occupations results in an according change in technological age. This variation in technological age drives the effects of technological age on both, wages and occupation change[50].

As explained in Section *4.2*, the wage regression uses log technological age so that one is added to all of the computer numbers in order to prevent having to take the log of the number zero. The term for technological age

$$[ln(1 + A_{jt}) - ln(1 + A_{j\tau})]$$

is then interacted with occupation dummies to create the term

$$[ln(1 + A_{jt}) - ln(1 + A_{j\tau})] * occupation_{ijt}$$

Finally, in order to conduct the occupation change regression, a dummy variable indicating if the person will leave the occupation in the next period had to be created. The variable works in a way that if the person will change their occupation in the next

[49] The occupational technological change can be found in Section *5.1.4*.
[50] As discussed in Section *4.2*, there are no other interaction effects in the estimation. Interaction effects featuring years and occupation would exclude the linear technological age variations from the estimation of the technological age effect.

period, the variable has a value of one, otherwise the value is zero. Looking at the decision to leave an occupation in the next period gives the analysis the opportunity to see whether technological age could give workers a reason to leave their occupation.

The only difference between the data used for the wage analysis and the data used for the occupation change analysis is that the dataset for the occupation change analysis has 11,030,551 observations (compared to the 11,012,285 observations utilized in the wage regressions). The about 18,000 observations more are the observations that have a daily wage of zero. For the wage regression, these observations were extremely disruptive, potentially influencing the results as they skewed the dependent variable. Yet, in the occupation change analysis, wage is not used as an explanatory variable. In fact, adding a wage variable makes it impossible to capture workers that leave their occupation due to technological age after a pregnancy or a sabbatical. Furthermore, not having to drop the observations with a daily wage of zero makes it possible to add a few more than 18,000 observations to the analysis.

As always, when working with data there are several issues one should keep in mind. The most prominent issue is the presence of the German reunification in 1990. This means that the East German States (Bundesländer) are missing from the data in the years before 1992. From 1992 onwards, all of Germany is present in the data. Since the regression controls for years and for state, this should not be a large issue regarding the results, yet the impact of technological age in the East German states could be different when compared to the West German states. Furthermore, as already mentioned, there is the fact that wage is reported on a daily basis. For most workers, this should not be an issue as they earn a similar wage each month, yet there might be cases where the daily wage might be unevenly impacted due to overtime or commission pay. Further smaller and more localized issues (by either time or place) can be found in Ganzer, Schmucker, vom Berge and Wurdack (2016).

Sections *5.2.1* to *5.2.3* have given an insight into which variables are included in the *SIAB Data* and what information they convey. Furthermore, the imputation of vocational training and wages was made clear as well as the calculation of technological age and the creation of occupation change in the next period. The next section gives a more in-depth overview over the variables in the *SIAB Data* by reporting some descriptive statistics of the dataset in general and the occupation variable more specifically. Since the data used for the wage and the occupation change analysis are almost exactly the same (the 18000-observation difference amounts to only about 0.001% of the data), the descriptive statistics in the next section are about the data used for the wage regressions. More in-depth information for the data that is used in the occupation change regressions is reported in Appendix A8.

5.2.4 Descriptive statistics *SIAB Data*

In this section, some descriptive statics are reported in order to give a better overview over the dataset. While the used variables should be clear in their theoretical conception, their distribution in the dataset is useful to keep in mind and allows for a better understanding of the data used. As stated in Section *5.2.1*, the dataset runs from 1979 to 2006 encompassing 11,012,285 observations from 971,510 individuals. This section gives a short overview over the non-log overall, between and within distribution of the variables, including mean and standard deviation, as well as the distributions of the logged variables used in the regression. The reason for including the non-log form of the variables for this overview is that giving an overview the log form is most likely not telling. This section is more so to give information about the data in its original form and to allow for a better understanding of the dataset. For this reason, the statistics also include variables not used for the regression, such as the share of females or German citizens in the dataset (both not applicable variables in a fixed effects regression). Furthermore, some interesting aspects of the data, descriptive statistics found in *Table 8: Descriptive statistics SIAB Data* are pointed out.

When looking at *Table 8*, one of the first things coming to mind is that only about 33 percent of the observations in the dataset are female. Furthermore, about 91 percent of the observations in the dataset are of German nationality. The average age is 38.3 with a standard deviation of 11.2. The average daily wage (not imputed) is 68.3 with a standard deviation of 31.1, showing that there is indeed quite a bit of variation in the wage variable. For this reason, *Figure 10* shows a kernel density plot of daily wage, which, not surprisingly, reveals a distribution skewed towards lower wages. Additionally, the days spent unemployed variable shows an overall average of 4.6 days spent unemployed with a standard deviation of 49.9 days. The minimum days spent unemployed are zero. Most workers were not unemployed at all during their working life, while some workers spent a considerable amount of time unemployed. The variable for vocational training shows that in fact most workers in the dataset have vocational training as their education indicated by a value of two and the variable for experience shows that the average years of experience in an occupation are 7.1 years with a maximum of 28 years (the entire length of the dataset). Finally, the variable measuring technological age, “ln_computeruse_change”, has an average of 0.2. Of course, technological age can also be negative when a worker changes from a technologically intensive occupation to a less technologically intensive occupation and reduces his/her technological age in the process, hence the negative minimal technological age.

Table 9 shows the number of observations per *KldB88*. Each occupation has a sufficient number of observations, as the occupations with the least observations are ceramic_glas (3) and woodworking (6) with 38,630 and 38,761 observations respectively. On the other hand, administration (24) more than doubles the next most observations with 2,216,256 observation and 20% of the overall observations.

More detailed information on the distribution of observations in the vocational training variable, state variable or age variable can be found in Appendix *A7* as well as the general description of observations across time in this panel set and the setup of the panel. Appendix *A8* reports the descriptive statistics shown in *Table 8* and *Table 9* again for the occupation change data including the extra used 18,000 observations. Overall, the variables largely show numbers that are expected. With finishing the data description, the next section reports, discusses and explains the regression results for the wage analysis. This analysis includes the regression of the *overall sample* of 1979-2006 as well as the three subsample regression of s*ubsample 79, subsample 90* and *subsample 00* for the years 1979-1989, 1990-1999 and 2000-2006 respectively.

Table 8: *Descriptive statistics SIAB Data*

Variable		Mean	Std. Dev.	Min	Max	Observations
personnumber	overall	854009.3	493146.8	1	1707228	N =11012285
	between		493027.4	1	1707228	n = 971510
	within		0	854009.3	854009.3	T-bar = 11.3352
formerjobs	overall	2.968986	2.697894	1	148	N =11012285
	between		2.136026	1	91.21429	n = 971510
	within		1.365696	-41.1487	65.38565	T-bar = 11.3352
female	overall	0.333822	0.471577	0	1	N =11012285
	between		0.490544	0	1	n = 971510
	within		0	0.333822	0.333822	T-bar = 11.3352
german	overall	0.911266	0.28436	0	1	N = 9530464
	between		0.308147	0	1	n = 802717
	within		0.082705	-0.05302	1.875551	T-bar = 11.8728
daily_wage	overall	68.30856	31.14114	1	172	N =11012285
(not imputed)	between		25.38796	1	172	n = 971510
	within		19.34842	-68.7914	210.7701	T-bar = 11.3352
lvl_of_performance	overall	2.222528	0.648918	1	4	N =11012285
	between		0.600813	1	4	n = 971510
	within		0.283031	-0.67033	5.115385	T-bar = 11.3352
days_unemployed	overall	4.587172	49.94098	0	8400	N =11012285
	between		42.5737	0	4930.95	n = 971510
	within		43.25364	-4602.71	5618.873	T-bar = 11.3352
industry	overall	7.313499	3.387984	1	13	N =11012285
	between		3.086748	1	13	n = 971510
	within		1.386322	-4.25793	18.88493	T-bar = 11.3352
year	overall	1993.03	7.854819	1979	2006	N =11012285
	between		7.069354	1979	2006	n = 971510
	within		5.605818	1972.03	2014.03	T-bar = 11.3352
vocTrain	overall	2.225984	1.027629	1	5	N =11012285
	between		1.004234	1	5	n = 971510
	within		0.306492	-1.63116	6.083127	T-bar = 11.3352
age	overall	38.30468	11.24988	17	62	N =11012285
	between		11.34273	17	62	n = 971510
	within		5.605818	17.30468	59.30468	T-bar = 11.3352
ln_wage	overall	4.139104	0.537563	0	7.414431	N =11012285
	between		0.481952	0	6.184258	n = 971510
	within		0.324198	-0.93822	6.816253	T-bar = 11.3352
KldB88	overall	20.07838	8.280794	1	31	N =11012285
	between		7.715561	1	31	n = 971510
	within		3.265867	-8.81051	48.49943	T-bar = 11.3352
employment_change	overall	0.028672	0.18814	-0.7	0.92	N =11012285
	between		0.100196	-0.7	0.92	n = 971510
	within		0.1698	-0.86466	1.12153	T-bar = 11.3352

Variable		Mean	Std. Dev.	Min	Max	Observations
ln_computeruse_change	overall	0.206154	0.186113	-0.64226	0.689367	N =11012285
(tech_age)	between		0.139443	-0.41855	0.667574	n = 971510
	within		0.129863	-0.39765	0.860741	T-bar = 11.3352
experience	overall	7.109792	5.868252	1	28	N =11012285
	between		3.420106	1	16	n = 971510
	within		4.593775	-6.39021	20.60979	T-bar = 11.3352
ln_age	overall	3.599849	0.308088	2.833213	4.127134	N =11012285
	between		0.31304	2.833213	4.127134	n = 971510
	within		0.158291	2.829641	4.30068	T-bar = 11.3352
ln_lvl_of_performance	overall	0.762395	0.262847	0	1.386294	N =11012285
	between		0.242203	0	1.386294	n = 971510
	within		0.122803	-0.57439	2.099179	T-bar = 11.3352
ln_formerjobs	overall	0.806681	0.720412	0	4.997212	N =11012285
	between		0.615245	0	4.471099	n = 971510
	within		0.351707	-2.59605	3.113393	T-bar = 11.3352
ln_experience	overall	1.579699	0.934139	0	3.332205	N =11012285
	between		0.639899	0	2.668673	n = 971510
	within		0.751872	-0.84494	3.127929	T-bar = 11.3352
state	overall	7.090718	3.333007	1	16	N =11012285
	between		3.453895	1	16	n = 971510
	within		0.795718	-6.97178	21.18163	T-bar = 11.3352

Note: Where applicable, overall, between and within mean, standard deviation, minimum and maximum per variable as well as number of observations including the variable, number of persons with value for the variable and average number of observations of the variable for one person.

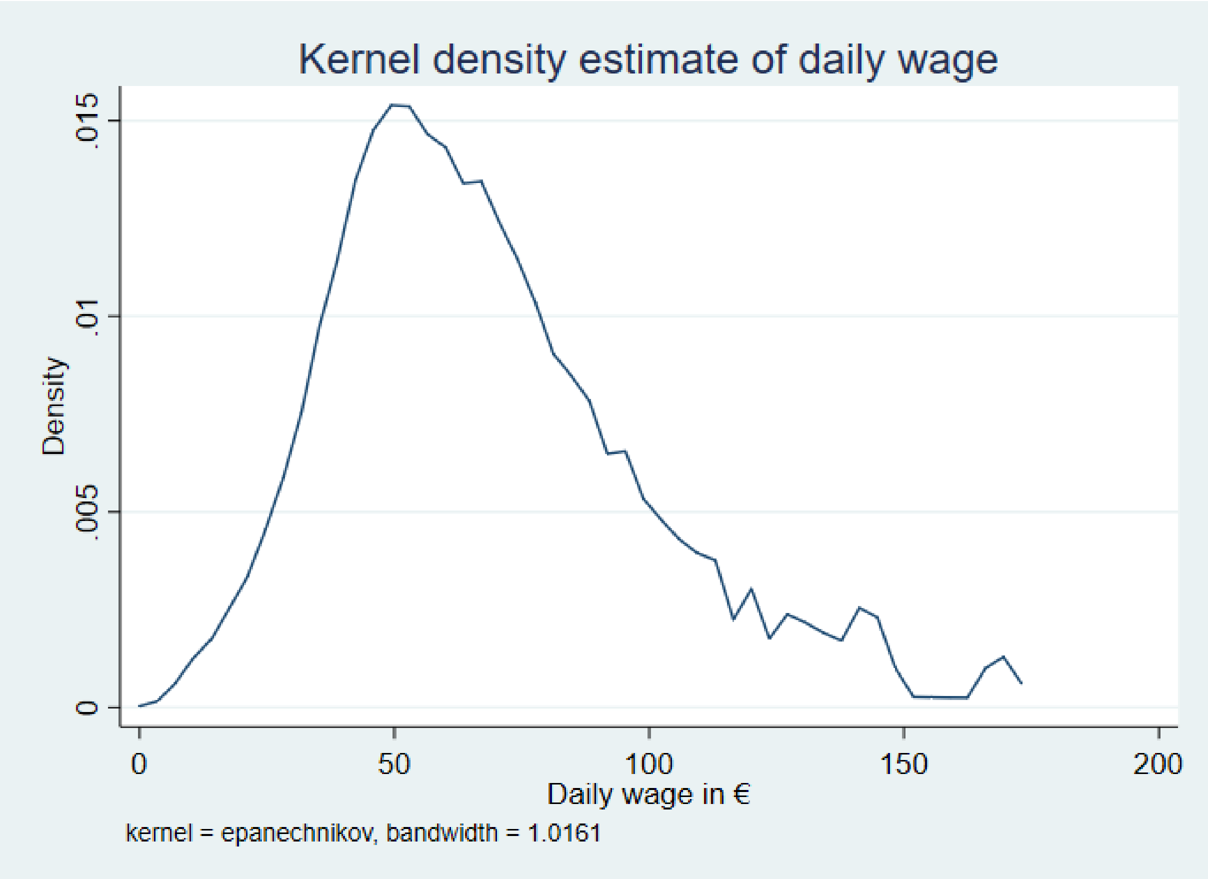

Figure 10: *Kernel density estimate of daily wage in Euro*

Table 9: *Observations per KldB88*

KldB88	Freq.	Percent	Cum.
agriculture_fishing (1)	193,731	1.76	1.76
miners_stone_workers (2)	77,698	0.71	2.46
ceramic_glas (3)	38,630	0.35	2.82
chemistry_synthetic_workers (4)	248,517	2.26	5.07
paper_print (5)	153,092	1.39	6.46
woodworking (6)	38,761	0.35	6.81
metal_works (7)	359,310	3.26	10.08
mechanics (8)	958,311	8.7	18.78
electricians (9)	346,968	3.15	21.93
assembly (10)	284,569	2.58	24.51
textile_clothing_leather_fur (11)	161,590	1.47	25.98
food (12)	340,242	3.09	29.07
construction (13)	535,651	4.86	33.94
interior_construction (14)	114,554	1.04	34.98
carpenter (15)	130,437	1.18	36.16
painter (16)	139,557	1.27	37.43
product_testing (17)	218,708	1.99	39.41
machinist (18)	123,017	1.12	40.53
engineer_math_chem (19)	322,619	2.93	43.46
technical_specilaist (20)	579,653	5.26	48.72
goods_merchants (21)	803,672	7.3	56.02
service_merchants (22)	454,812	4.13	60.15
traffic (23)	981,169	8.91	69.06
administration (24)	2,216,256	20.13	89.19
regulatory_safety (25)	178,757	1.62	90.81
writing_art (26)	107,584	0.98	91.79
healthcare (27)	564,402	5.13	96.91
social_education_science (28)	340,018	3.09	100
Total	11,012,285	100	

6 Wage analysis

The wage analysis section covers the results of how technological age affects workers' wages utilizing the regression function described in Section *4.2*. First, the regression results of the *overall sample* ranging from 1979-2006 are reported and discussed, showing how technological age impacted wages across the *overall sample* period. However, the *overall sample* includes 38 years, and the linear regression model imposes a linear effect of technological age for the entire sample. In order to check whether technological age had a differing impact in different time periods, the *overall sample* is split into three subsamples, *subsample 79, subsample 90* and *subsample 00* covering the years 1979-198, 1990-1999 and 2000-2006 respectively. The same regression model is then again used for each subsample and this section then reports and discusses the results of the subsample regressions.

This analysis only features regressions estimating the wage impact of technological age on an occupational basis. The concept of technological age as well as the theoretical model of Section *4.1* are all based on the concept that technological age has a differing impact in different occupations. However, in reference to the literature looking at the computer usage of older workers[51] regardless of occupation, Appendix *A11.i* shows the regression results for a non-occupation specific effect of technological age on wages. In the terms of the model discussed in Section *4.2*, the regression estimates the impact of technological age θ without regard for the occupation j. Nevertheless, this thesis explores the impact of technological age on an occupational level, starting with the results of the *overall regression*.

[51] This literature includes for example Bertschek and Meyer (2009), Borghans and Ter Weel (2002), Czaja and Sharit (1993), de Koning and Gelderblom (2006), Meyer (2011), Morris and Venkatesh (2000) and Schleife (2006)

6.1 Regression results *overall sample*

This section covers the report and discussion of the wage regression covering the *overall sample* period of 1979-2006. The regression results can be found in *Table 10: Regression (1), the impact of log technological age on log wages, overall sample.* As stated in Section *4.2*, the goal is to estimate the effect of technological age on wages for each occupation and to test Hypothesis 2, namely that technological age decreases workers' wages. There are 28 different occupations for which the wage effect of technological age must be estimated, leading to 28 coefficients to analyze. These 28 coefficients already make *Table 10* cumbersome, which is why the full regression output, including the control variables, is found in Appendix *A11.ii*. Furthermore, since initially it is difficult to grasp the effect of 28 coefficients at the same time, the next section reports the marginal effects in graphical form (*Figure 11*). In order to give a better overview over the coefficients, the marginal effects are ordered by size. While this is a bit unconventional, it provides the opportunity to easier comprehend the marginal effects. This method is used throughout this analysis. In the following, the regression results from *Table 10* are reported and described.

The first interesting fact to note is that the regression uses 11,012,285 observations and has an adjusted R-squared of 0.5218. All coefficients are significant at the one percent level, except for the coefficient for the woodworking (6) occupation, which is insignificant. The insignificance of woodworking is not surprising however, as this occupation had almost no technological change over the entire timeframe (as can be seen in *Figure 6*). Secondly, eight occupations have positive coefficients: electricians (9), engineer_math_chem (19), technical_specilaist (20), goods_merchants (21), service_merchants (22), administration (24), writing_art (26) and social_education_science (28). This naturally means a positive effect of technological age on wages. The coefficients for the other occupations are negative supporting Hypothesis 2.

Considering this model is a log-log regression, a 10 percent increase in technological age in the agriculture and fishing occupations leads to a 2.747 percent decrease in daily wage. The occupation with the largest negative coefficient is construction (13) with -0.7668 and the occupation with the largest positive coefficient is service_merchants (22) with 0.3714. However, the coefficient for construction (13) is quite a bit more negative than the coefficient for next largest negative occupation miners_stone_workers (2) with -0.4973.

As the marginal effects for each occupation except woodworking (6) are strongly significant, it can be concluded that technological age indeed affects wages. Alas, not all is as Hypothesis 2 would predict. About 28 percent of the occupations show a positive effect of technological age on wages (8 out of 28). While there are many possible explanations, a possible reason is that in the eight occupation with positive coefficients, human capital does not depreciate due to technological change. It is possible that, training for the employees reversed the effect of technological age in the occupations with a positive effect of technological age on wages, making workers more efficient in the use of technology and indeed increasing human capital. If that were the case, the technological age variable would no longer measure human capital depreciation due to technological change but rather productivity increase due to human capital appreciation. Alas, the *SIAB Data* sample used does not give information on training and detailed technological change data is also not readily available. Thus, for now, any explanation is purely speculative, and it is difficult to explain the positive coefficients satisfactorily.

For about 71 percent or 20 out of the 28 occupations, Hypothesis 2 seems to hold true. There is a negative marginal effect of log technological age on log wage in each of the occupations. Workers' human capital is depreciating due to technological change and this negatively affects their wages. As mentioned above, there are still large differences between the sizes of the marginal effects of log technological age on log wages. Several occupations show a larger negative influence of technological age [agriculture_fishing (1), miners_stone_workers (2) ceramic_glas (3) textile_clothing_leather_fur (11) food (12) construction (13) interior_construction (14) carpenter (15) painter (16) traffic (23)] ranging from -0.7668 to -0.2747. Other occupations [chemistry_synthetic_workers (4) paper_print (5) metal_works (7) mechanics (8) assembly (10) product_testing (17) machinist (18) regulatory_safety (25) healthcare (27)] show a much smaller effect ranging from -0.1575 to -0.0528. Furthermore, it has to be clear that this is only the marginal effect of log technological age on log wages. These effects do in no way state that people with larger technological age take wage cuts regularly. Overall, when taking other factors like experience, age, etc. into account, people with rising technological age might see their wages increase overall. However, the increase is then smaller than it would be without the impediment of technological age. A negative effect of technological age on wages does not have to mean declining wages overall.

Following *Table 10*, the next section graphically presents the coefficients to give a better overview. First, the coefficients are ordered by size along the x-axis and their size shown in a bar graph along the y-axis. Second, the coefficients are put into context of total technological change that took place in each occupation. From this, further discussion of the results evolves, as it makes it easier to give a more general interpretation of the coefficients.

Table 10: *Regression (1), the impact of log technological age on log wages, overall sample*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)
ln_agriculture_fishing (1)	-0.2744*** (0.0113)
ln_miners_stone_workers (2)	-0.4999*** (0.0173)
ln_ceramic_glas (3)	-0.3306*** (0.0221)
ln_chemistry_synthetic_workers (4)	-0.1037*** (0.0070)
ln_paper_print (5)	-0.0939*** (0.0104)
ln_woodworking (6)	-0.1004 (0.0919)
ln_metal_works (7)	-0.0845*** (0.0055)
ln_mechanics (8)	-0.0816*** (0.0047)
ln_electricians (9)	0.0448*** (0.0067)
ln_assembly (10)	-0.1110*** (0.0078)
ln_textile_clothing_leather_fur (11)	-0.4421*** (0.0213)
ln_food (12)	-0.4445*** (0.0134)
ln_construction (13)	-0.7675*** (0.0122)
ln_interior_construction (14)	-0.4687*** (0.0147)
ln_carpenter (15)	-0.4005*** (0.0119)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)
ln_painter (16)	-0.3436***
	(0.0123)
ln_product_testing (17)	-0.0770***
	(0.0087)
ln_machinist (18)	-0.0529***
	(0.0090)
ln_engineer_math_chem (19)	0.3420***
	(0.0088)
ln_technical_specilaist (20)	0.3113***
	(0.0054)
ln_goods_merchants (21)	0.0363***
	(0.0071)
ln_service_merchants (22)	0.3709***
	(0.0075)
ln_traffic (23)	-0.3413***
	(0.0060)
ln_administration (24)	0.1736***
	(0.0043)
ln_regulatory_safety (25)	-0.0955***
	(0.0097)
ln_writing_art (26)	0.1685***
	(0.0145)
ln_healthcare (27)	-0.1589***
	(0.0070)
ln_social_education_science (28)	0.1339***
	(0.0080)
Constant	-1.0037***
	(0.0167)
N	11,012,285
R-sq	0.5218

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

6.2 Regression discussion *overall sample*

In this section, the coefficients from *Table 10* above are depicted in two graphs. First, *Figure 11* is a bar graph that shows the marginal effects from the regression above in increasing order. The increasing sequence is chosen to make a comparison of the size of the marginal effect in each occupation with regards to the other occupations much simpler. Second, *Figure 12* depicts the total technological change in each occupation across the *overall sample* on the x-axis and the marginal effects from regression (1) on the y-axis. Because this graph shows a clear correlation between the total technological change in each occupation and the marginal effects of technological age on wages, the correlation coefficient is also provided to quantify the correlation.

Figure 11 depicts the size of the coefficients of *Table 10* and the standard error on the y-axis and orders the occupations according to the size of the coefficient in increasing order along the x-axis. It thus gives an overview of the marginal effects of log technological age on log wages per occupation. This bar graph makes the descriptions and division of the effects from Section *6.1*, namely occupations with strong negative effect, occupations with small negative effect and occupations with positive effect more obvious. As could be seen from the regression output already, most coefficients are negative, in accordance with Hypothesis 2, while a few are positive. More interestingly, the occupations that have positive coefficients seem to have some characteristics in common, as do the one that have negative.

The occupations with positive marginal effects are electricians (9), engineer_math_chem (19), technical_specilaist (20), goods_merchants (21), service_merchants (22), administration (24), writing_art (26) and social_education_science (28). All these occupations seem to be technologically intensive and generally employ higher educated workers. The occupations that have a clear negative marginal effect are agriculture_fishing (1), miners_stone_workers (2), ceramic_glas (3), textile_clothing_leather_fur (11), food (12), construction (13), interior_construction (14), carpenter (15), painter (16) and traffic (23). These occupations are generally more manual labor intensive, have experienced less technological change and probably employ less highly educated workers. Overall, there seems to be the trend that workers in more technologically intensive occupations have less of a detriment (or even a bonus) from technological age than workers working in occupations experiencing less technological change.

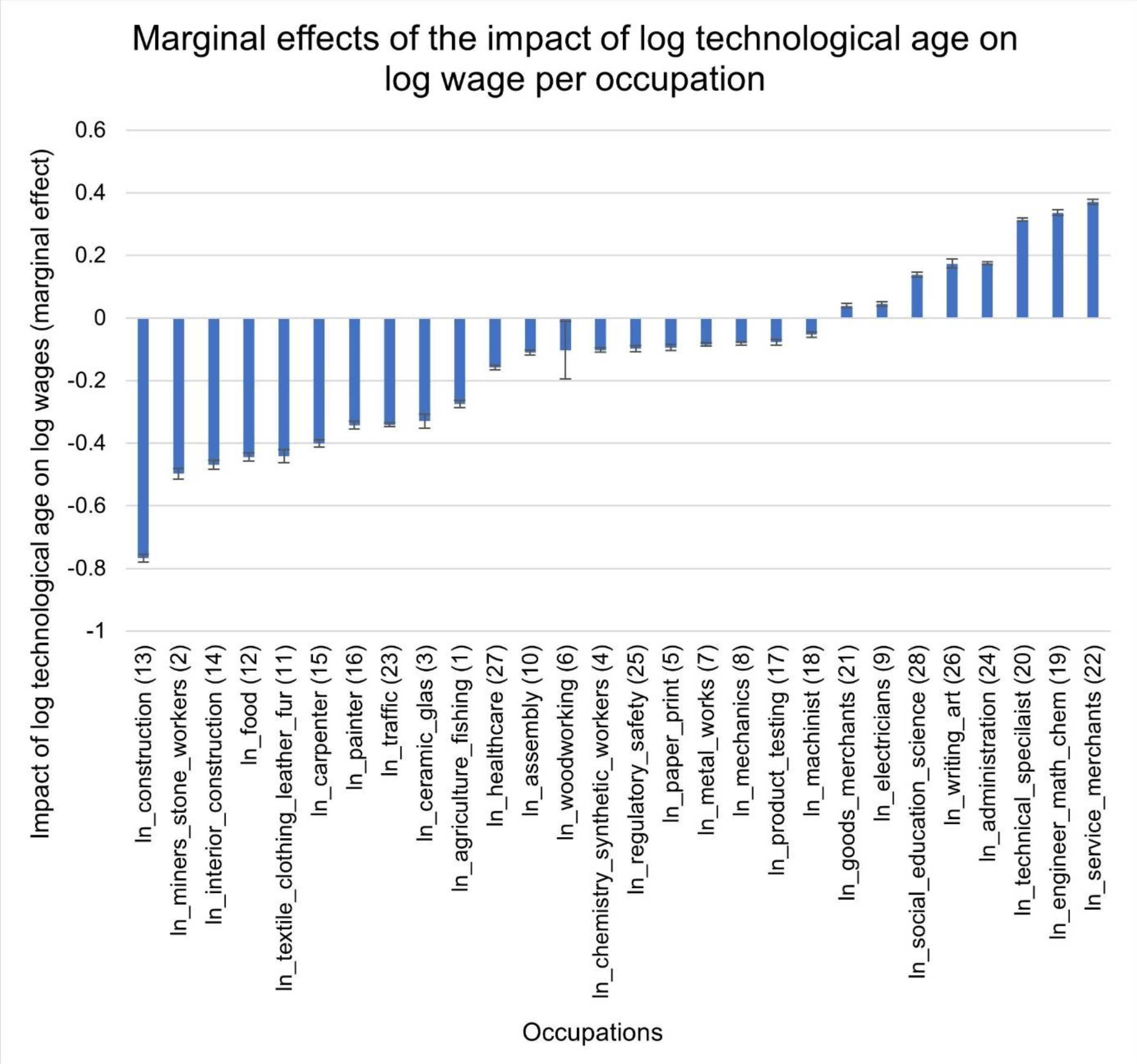

Figure 11: *Marginal effects of the impact of log technological age on log wage per occupation*

Note: Marginal effects of regression (1) ordered by size. Including standard errors.

Figure 12 confirms this suspicion as it depicts the size of the marginal effect of the impact of log technological age on log wages per occupation on the y-axis and the total technological change that happened in each occupation between 1979 and 2006 on the x-axis. It is obvious that with increasing technological change during the timeframe, the impact of log technological age on log wages becomes more and more positive. In fact, the trend shown by *Figure 12* is almost linear. The outlier at the left is the woodworking (6) occupation, which has not experienced any technological change and is statistically insignificant in the regression. When omitting the outlier of wood-working and looking at the linear correlation, the correlation between the impact of log wages on log technological age per occupation and the total technological change per occupation is 0.8968, further showing that an almost perfect linear relationship exists. The linear correlation can be found in *Table 11*.

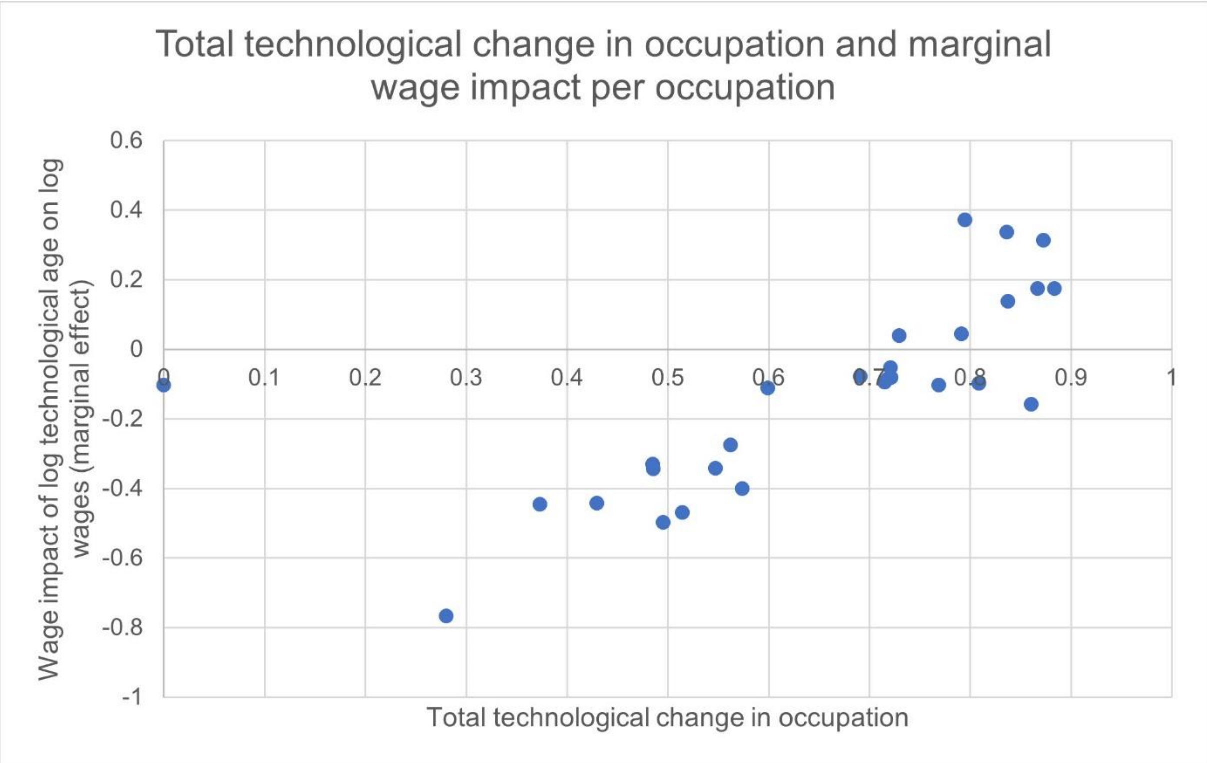

Figure 12: *Total technological change in occupation and marginal wage impact per occupation*

Marginal effects of regression (1) and overall technological change per occupation from Table A3 to *Table A6.*

Table 11: *Linear correlation between the marginal effects of regression (1) and technological change per occupation*

Correlation between	**Sample Period**	**Correlation**
marginal effects wage impact	*overall sample*	0.8968
technological change	*overall sample*	

Note: The correlation does not include the observation for woodworking (6).

However, while *Figure 12* confirms that occupations with more overall technological change have a more positive impact of log technological age on log wages, the interpretation is not completely straightforward. As mentioned in Section *6.1*, an easy explanation would be that occupations with more technological change are simply more used to technological change and can reverse the human capital depreciation of their workers more effectively through training their workers. If this training were to increase the workers' human capital instead of having it decreased by technological age, the positive effects would make sense. Furthermore, most occupations with a lot of technological change experienced this change earlier than the occupation with less technological change. The effect seen from the occupations with a lot of technological change could thus be similar in the other occupations in a few years. What makes this unlikely is the following regression analysis in Section *6.3*, splitting the sample into three different timeframes and analyzing the effects of log technological age on log wages per timeframe. A problem with *Figure 12* is that the marginal effect is estimated for the sample period of 28 years, during which it cannot vary. Technologically speaking, 28 years is a very long timeframe where the impact of technological age on wages could have changed. Something else one must be very careful about is the difference between technological change and technological age. *Figure 12* depicts the marginal effects and the total technological change per occupation. This does not mean that only people that have a high technological age work in the occupations that have experienced a lot of technological change. Workers could have changed occupations when they felt like they cannot keep up with technological change and could be driving this distribution (this effect is analyzed in Section *8 Occupation change analysis*). Furthermore, if occupations hired workers during or after the time technology changed rapidly, those workers would have a low technological age.

Overall, it can be said that there is a mostly negative effect of log technological age on workers log wages. In most occupations, workers receive less wages due to technological age. Alas, in some occupations technological age seems to have a positive effect on wages when looking at the whole sample period. The size of the effect of log technological age on log wages is correlated with total technological change per occupation. The more technological change an occupation has experienced over the timeframe of the sample, the more positive (or less negative) is the influence of log technological change on log wages. This regression however cannot control for mitigating factors such as the training of workers and does not account for workers changing occupations to mitigate the effect of technological age as well as differences of the influence of technological age throughout the timeframe of this sample. The latter, different impacts of technological age on wages in different time periods are explored in the next section when the sample period is split up into the time periods *subsample 79*, *subsample 90* and *subsample 00*, running the regression of Equation *(7)* again for each timeframe.

6.3 Regression results *subsample 79, subsample 90* and *subsample 00*

As mentioned in Section *6.2*, the sample period of 28 years is a long timeframe when looking at technological change. Technology has evolved greatly in the last decades and there is no telling if the influence of technological change or technological age were constant over such a long timeframe. For this reason, the sample period is split into three subsamples and the analysis from Sections *6.1* and *6.2* are repeated correspondingly. This section covers the report and interpretation of the regression from Section *6.1* split into three time periods: 1979-1989, 1990-1999 and 2000-2006 called "*subsample 79", "subsample 90"* and *"subsample 00"* respectively. The results are reported similarly to the results in the last section. First, the regression output table with results from the three time period regressions are reported and discussed. The next section then reports a graph showing the marginal occupational effects of log technological age on log wage for each time period. The next section also provides a graph showing the correlation between the marginal effects of log technological age per occupation and total technological change per occupation. The regression outputs of the three time periods are reported alongside the results for *overall sample* (1979-2006). Furthermore, the graphs also show the marginal effects of the *overall sample* alongside the marginal effects of the subsample timeframes for reference.

Splitting the dataset into smaller time periods should give an insight into whether the impact of log technological age on log wages stays constant over the sample. Since technological change was also not taking place at a constant rate in all occupations, it would be fair to assume that in different time periods workers were differently affected by technological age. It could also be that occupations learned how to deal with the technological change in a more efficient way and thus changed the impact of technological age in the later years. On the other hand, the rise of the internet around the turn of the millennia could have led to new challenges regarding technological age. The split of the *overall sample* into the subsamples *subsample 79, subsample 90* and *subsample 00* was designed to create three comparably long subsamples while keeping the growing internet usage at the turn of the millennium in mind[52].

[52] A graph showing internet usage can be found in Appendix *A12*.

Table 12: *Regressions (1), (2), (3) and (4), the impact of log technological age on log wages, overall sample, subsample 79, subsample 90 and subsample 00*

Dependent variable: log daily wage	Occupation specific coeffi-cients of log tech age *overall sample* (1)	Occupation specific coeffi-cients of log tech age *subsample 79* (2)	Occupation specific coeffi-cients of log tech age *subsample 90* (3)	Occupation specific coeffi-cients of log tech age *subsample 00* (4)
ln_agriculture_fishing (1)	-0.2747***	-0.1796	0.2614***	-0.4193***
	(0.0113)	(0.1630)	(0.0429)	(0.0180)
ln_miners_stone_workers (2)	-0.4973***	-0.5950***	-0.3586	-0.2791***
	(0.0172)	(0.1669)	(0.2079)	(0.0251)
ln_ceramic_glas (3)	-0.3295***	-0.0886	-0.0906*	-0.4717***
	(0.0221)	(0.2955)	(0.0428)	(0.0516)
ln_chemistry_synthetic_workers (4)	-0.1028***	0.4270***	0.0499*	-0.2104***
	(0.0070)	(0.0325)	(0.0223)	(0.0135)
ln_paper_print (5)	-0.0943***	0.3009***	0.0874*	-0.3841***
	(0.0104)	(0.0336)	(0.0406)	(0.0216)
ln_woodworking (6)	-0.1033	-0.7614**	-0.0958	-0.1971
	(0.0920)	(0.2592)	(0.1444)	(0.1475)
ln_metal_works (7)	-0.0850***	0.0633	-0.3130***	-0.1330***
	(0.0055)	(0.0583)	(0.0580)	(0.0078)
ln_mechanics (8)	-0.0810***	0.3213***	0.1729***	-0.2240***
	(0.0047)	(0.0362)	(0.0206)	(0.0078)
ln_electricians (9)	0.0452***	0.3947***	0.2364***	-0.2067***
	(0.0067)	(0.0246)	(0.0197)	(0.0155)
ln_assembly (10)	-0.1107***	-0.2699***	-0.0071	-0.2210***
	(0.0078)	(0.0620)	(0.0454)	(0.0114)
ln_textile_clothing_leather_fur (11)	-0.4416***	-1.0598***	-0.1720*	-0.4072***
	(0.0213)	(0.1501)	(0.0793)	(0.0266)
ln_food (12)	-0.4447***	-0.7943***	0.1564*	-0.5231***
	(0.0133)	(0.1199)	(0.0642)	(0.0204)
ln_construction (13)	-0.7668***	-1.0211***	-0.2442***	-0.6716***
	(0.0122)	(0.1085)	(0.0570)	(0.0204)
ln_interior_construction (14)	-0.4682***	-0.6219***	-0.0829	-0.5075***
	(0.0147)	(0.1347)	(0.0672)	(0.0222)
ln_carpenter (15)	-0.4003***	-0.0738	0.0121	-0.5193***
	(0.0119)	(0.1012)	(0.0444)	(0.0194)
ln_painter (16)	-0.3426***	-0.1234	0.2359*	-0.3610***
	(0.0123)	(0.1441)	(0.0984)	(0.0196)
ln_product_testing (17)	-0.0773***	0.1956***	0.1794***	-0.2417***
	(0.0087)	(0.0349)	(0.0369)	(0.0175)
ln_machinist (18)	-0.0528***	0.3608***	0.3222***	-0.1435***
	(0.0090)	(0.0636)	(0.0539)	(0.0135)
ln_engineer_math_chem (19)	0.3367***	0.5615***	0.8318***	-0.1514***
	(0.0090)	(0.0170)	(0.0236)	(0.0370)
ln_technical_specilaist (20)	0.3143***	0.7065***	0.5092***	-0.1634***
	(0.0054)	(0.0120)	(0.0139)	(0.0255)
ln_goods_merchants (21)	0.0389***	0.4009***	0.4187***	-0.3603***
	(0.0071)	(0.0223)	(0.0167)	(0.0163)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age *subsample 79* (2)	Occupation specific coefficients of log tech age *subsample 90* (3)	Occupation specific coefficients of log tech age *subsample 00* (4)
ln_service_merchants (22)	0.3714***	0.5586***	0.7636***	-0.2162***
	(0.0075)	(0.0112)	(0.0220)	(0.0310)
ln_traffic (23)	-0.3411***	-0.2268***	0.1018***	-0.4014***
	(0.0060)	(0.0418)	(0.0273)	(0.0107)
ln_administration (24)	0.1746***	0.3492***	0.6224***	-0.1918***
	(0.0043)	(0.0078)	(0.0130)	(0.0216)
ln_regulatory_safety (25)	-0.0975***	0.2721***	0.2573***	-0.3206***
	(0.0097)	(0.0301)	(0.0200)	(0.0376)
ln_writing_art (26)	0.1741***	0.4520***	0.5039***	-0.2203***
	(0.0144)	(0.0349)	(0.0344)	(0.0511)
ln_healthcare (27)	-0.1575***	-0.0034	0.1975***	-0.3905***
	(0.0070)	(0.0304)	(0.0119)	(0.0221)
ln_social_education_science (28)	0.1381***	0.5532***	0.5002***	-0.1896***
	(0.0079)	(0.0399)	(0.0167)	(0.0214)
Constant	-1.0005***	-2.6854***	-0.5272***	-0.9607***
	(0.0167)	(0.0288)	(0.0314)	(0.0560)
N	11,012,285	3,830,276	4,360,117	2,821,892
R-sq	0.5218	0.3935	0.2648	0.1033

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

As before, only the occupation specific marginal effects of technological age are reported here. The full regression outputs can be found in Appendix *A11.iii*. The regression outputs, reported in *Table 12: Regressions (1), (2), (3) and (4), the impact of log technological age on log wages, overall sample, subsample 79, subsample 90 and subsample 00*, are described in chronological order. First, regression (2) the regression covering *subsample 79*, includes 3,830,276 observations and has an R-squared of 0.3935. 22 out of 28 coefficients of log technological change variables are statistically significant Alas, the coefficients for agriculture_fishing (1), ceramic_glas (3), metal_works (7), carpenter (15), painter (16) and healthcare (27) are not statistically significant. Not only are more coefficients statistically insignificant compared to regression (1), covering the *overall sample*, but there are overall more positive coefficients. Regression (1) had eight positive and nineteen negative coefficients (one insignificant); regression (2) has only 8 negative coefficients and 14 positive coefficients. The largest negative coefficient in regression (2) is the coefficient of textile_clothing_leather_fur

(11) with -1.0613; the largest positive coefficient is technical_specilaist (20) with 0.7049. Those effects are a bit larger than the effects from regression (1). Regression (2) has thus overall more positive and larger coefficients of technological age, further contrasting Hypothesis 2.

Regression (3), covering *subsample 90* uses 4,360,117 observations and has an R-squared of 0.2648. Regression (3) has twenty-three statistically significant and five statistically insignificant coefficients [miners_stone_workers (2), woodworking (6), assembly (10), interior_construction (14) and carpenter (15)]. Furthermore, regression (3) only has 4 negative coefficients and 19 positive coefficients; the rest of the technological age coefficients is insignificant. Compared to regression (1), the number of negative coefficients in regression (3) is very small. In *subsample 90*, log technological age seems to have a mostly positive influence on log wages. The largest negative coefficient is the one for construction (13) with -0.2493 and the largest positive coefficient is the one for engineer_math_chem (19) with 0.8427. Especially the positive range of coefficients is larger than in regression (1).

Regression (4), covering *subsample 00* utilizes 2,821,892 observations and achieves an R-squared of 0.1033, which is much lower than the previous regressions. Interestingly, coefficients for all occupations except woodworking (6) are statistically significant, comparable with regression (1). Furthermore, all coefficients are negative, ranging from the coefficient for construction (13) with -0.6657 to metal_works (7) with -0.1314. The fact that all marginal effects are negative is very curious. For one it means that most of the negative coefficients in regression (1) are driven by *subsample 00*. Also, it seems that while during *subsample 90* there was almost no negative influence of log technological age on log wages, during *subsample 00* log technological age had a negative impact on log wages in every occupation [except for woodworking (6)]. This could make sense for several reasons. For one, technological change quickened in most occupations after 1999[53]. In addition, as discussed already, the rise of the internet in this timeframe could have served as further human capital depreciation and thus lead to an even bigger experienced technological age than reported. Furthermore, regression (4) fully supports Hypothesis 2, giving more credit to the concept of human

[53] See *Figure 6* to *Figure 9* in Section *5.1.4 Technological progression according to BIBB Data*.

capital depreciation due to technological change hurting workers, especially in recent times.

Overall, splitting the sample provides very diverse results. The impact of log technological age on log wages is estimated to be more so positive rather than negative in the first two subsamples. Especially in *subsample 90*, technological age seems to have had a positive impact on wages. The results of *subsample 00* are completely different. In all occupations, log technological age had a negative effect on log wages. This could be either due to the increased technological change in this timeframe or maybe due to further changing technology with the rise of the internet in the workplace. The next section covers the graphs of the marginal effects of the different regression in much the same way Section *6.2* did. This section also attempts to give further interpretation to the results and show the regression coefficients of all three subsample regression in relation to total technological change in each occupation during the timeframe. In order to provide further context, the regression results from regression (1) are always included in the graphs.

6.4 Regression discussion *subsample 79, subsample 90* and *subsample 00*

This section, similar to Section *6.2*, reports the marginal effects of regression (2) – (4) in graphical form. Also similar to Section *6.2*, the marginal effects are ordered by size per occupation on the x-axis and the size of the marginal effect are reported on the y-axis. However, in order to give more context, the marginal effects from regression (1) are also reported and are ordered according to the results from the sample regression in *Figure 11*. As there are three timeframes, there are three graphs with marginal effects (*Figure 13* - *Figure 15*), depicting each timeframe separately. The three graphs are then described individually. Finally, the marginal effects of regression (1) – (4) are shown in a graph with the marginal impact of log technological age on log wages on the y-axis and the total technological change per occupation in the respective time period on the x-axis, showing the correlation between the impact of log technological age and total technological change per time period. To illustrate this correlation further, the correlation coefficients showing the linear correlation between the marginal impact of log technological age on log wages and the total technological change per occupation in the respective time period are also reported.

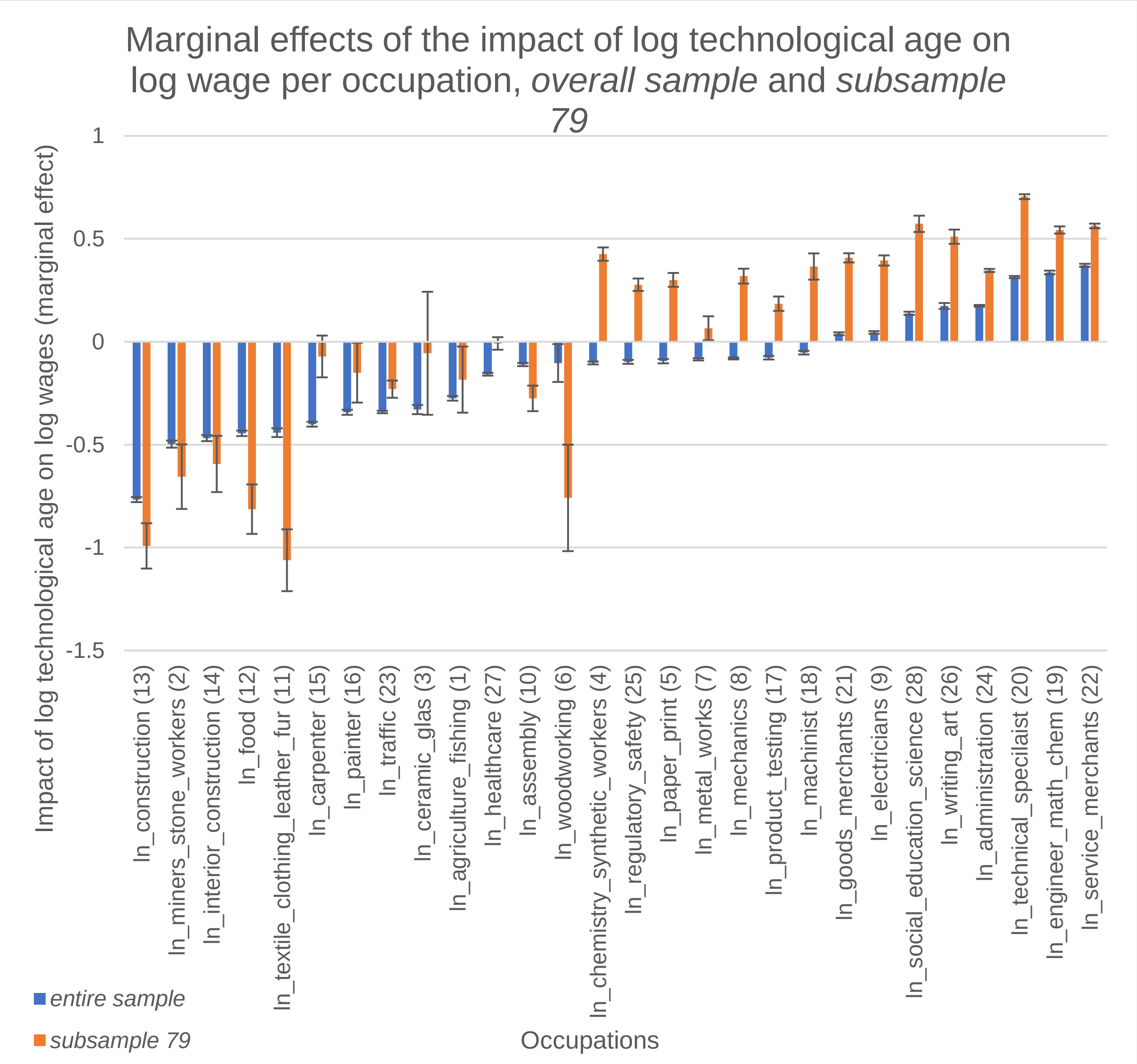

Figure 13: *Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 79*

Note: Marginal effects of regression (1) and regression (2), ordered by size of marginal effects in regression (1) Including standard errors.

Figure 13 shows the marginal effects of the impact of log technological age on log wages in the timeframes *subsample 79* and the *overall sample*. The ordering of the marginal effects is dependent on the effects from regression (1) of the *overall sample*. The marginal effects of the *overall sample* regression are thus reported increasing in size with the corresponding marginal effects from the *subsample 79* regression. This allows straightforward comparison between the marginal effects from the *overall sample* and the *subsample 79* regressions. While there are more positive marginal effects in the *subsample 79* than in the *overall sample* period, there also are some similarities. Almost all of the negative marginal effects from *subsample 79* are on the left-hand side with the exception of woodworking, which is not significant in the overall sample regression. Furthermore, all positive marginal effects are situated towards the right-hand side of the graph. Of course, this intuitively makes sense, as some of the distribution of the coefficients in the *overall sample* regression is driven by the *subsample 79* time period. Another fact that comes to mind is the larger size of the marginal effects from the *subsample 79* regression when compared to the *overall sample* regression. Overall, it can be said that the distribution is somewhat similar between the two regressions, with the *subsample 79* regression having larger and more positive effects. Of course, in many occupations, computerization was only stating in this time period. Many workers would not have a large amount of technological age amassed, which might influence the results. Technology driven human capital depreciation might not yet have been very strong.

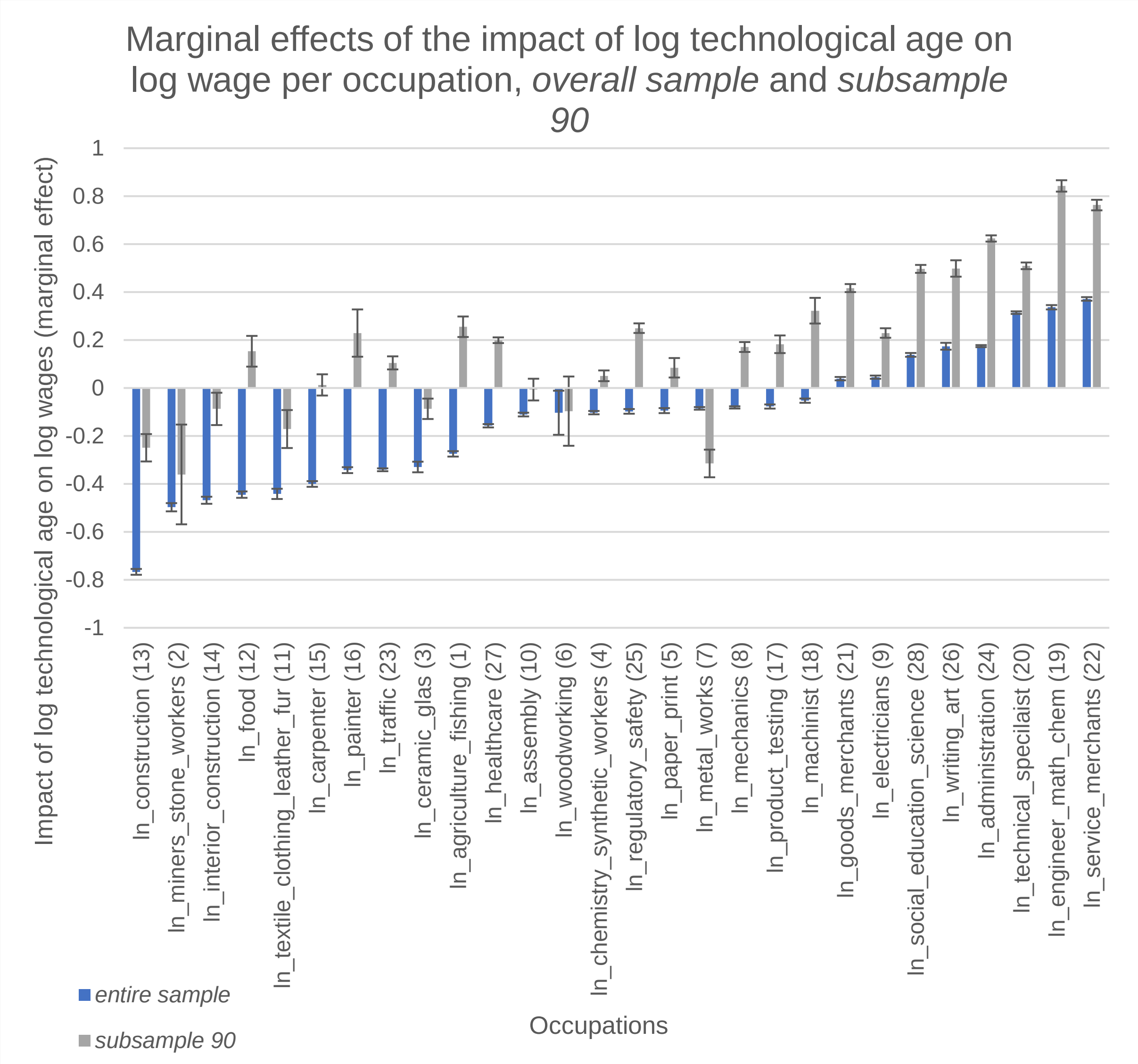

Figure 14: *Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 90*

Note: Marginal effects of regression (1) and regression (3), ordered by size of marginal effects in regression (1) Including standard errors.

Figure 14 shows the marginal effect of the impact of log technological age on log wages in the *subsample 90* [regression (3)] and *overall sample* [(regression (1)] time periods. As before, the ordering of the marginal effects is dependent on the effects from regression (1) of the *overall sample*, ordering them in increasing size allowing easier comparison. The most striking observation here is that almost all marginal effects from the *subsample 90* regression are positive. While the more positive marginal effects are on the right-hand side of the graph, the similarities between the marginal effects of the two regressions end there. The positive marginal effects are much larger in the *subsample 90* regression compared to the *overall sample* regression. Not only does it seem that log technological age has an overall positive impact in *subsample 90* timeframe, the positive impact is also much larger than compared to the *overall sample*.

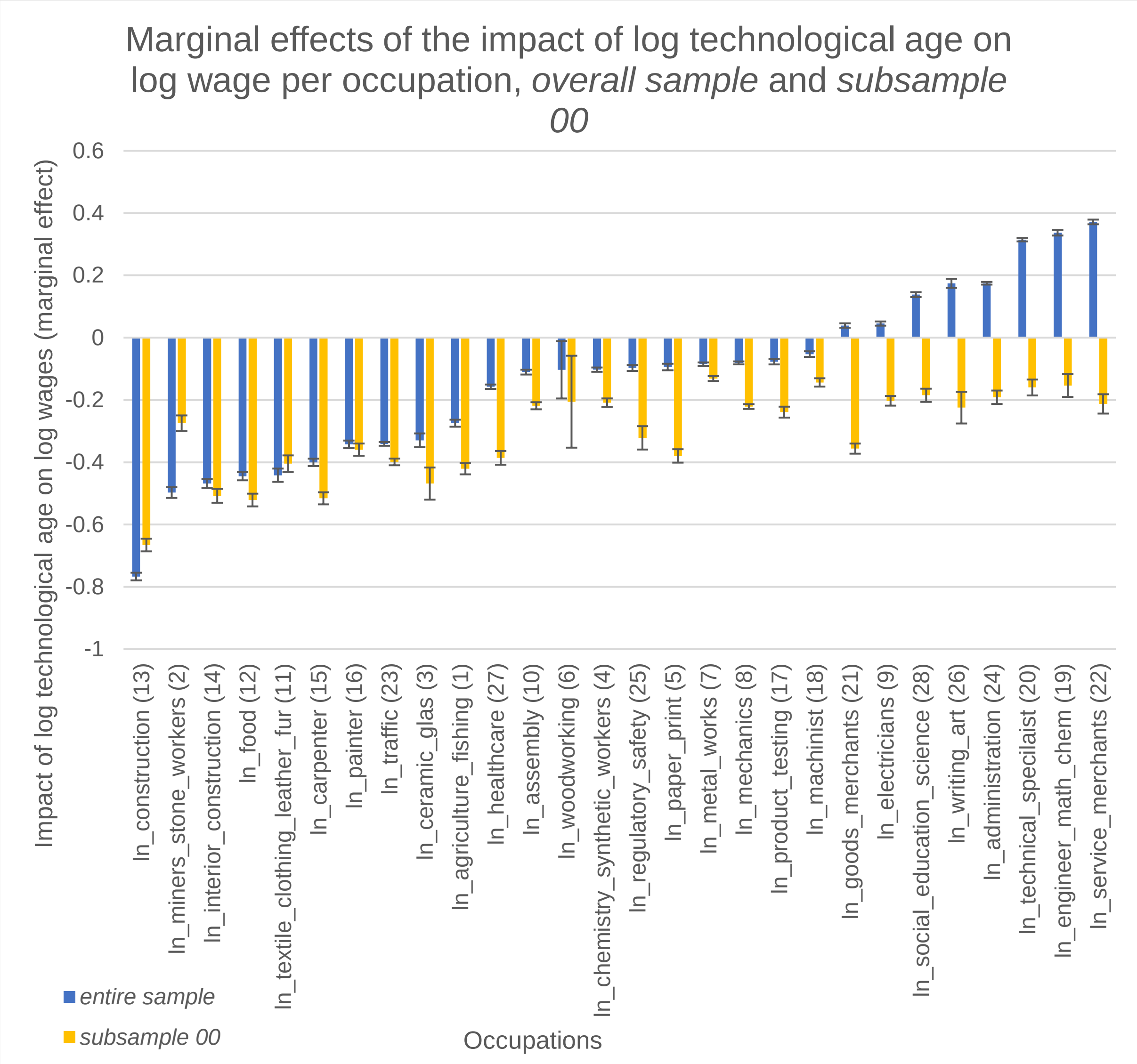

Figure 15: *Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 00*

Note: Marginal effects of regression (1) and regression (4), ordered by size of marginal effects in regression (1). Including standard errors.

Figure 15 shows the marginal effect of the impact of log technological age on log wages in the *subsample 00* and *overall sample* timeframes. As in the last two figures, the ordering of the marginal effects is dependent on the effects from regression (1) of the *overall sample*, ordering them in increasing size for easier comparison. Naturally, the first thing that springs to mind is that all marginal effects in the *subsample 00* are negative. Secondly, many of the marginal effects, especially on the left-hand side are similar in size compared to the marginal effects from the *overall sample*. Also, the marginal effects of the *subsample 00* regression are more negative on the left-hand side. The largest difference between the regressions is in the effects that are positive in the *overall sample* regression from in the occupations paper_print (5) and regulatory_safety (25). Since the occupations with less overall technological change in the *overall sample* period are situated on the left-hand side of the graph (as established in Section *6.2*), one might conclude that in *subsample 00* the negative impact of log technological age on log wages is again higher for occupations which have experienced less overall technological change, as the more negative marginal effects here are also situated on the left hand side. However, many occupations that experienced a lot of technological change across the *overall sample* period started experiencing this change much earlier than the rest of the occupations, while the occupations that did not have as much technological across the *overall sample* started experiencing technological change much later[54]. This leads to a situation where the impact of log technological age on log wages is not as clearly linked to overall experienced technological change per occupation in *subsample 00*.

[54] The technological change graphs for each occupation were reported in Section *5.1.4* as *Figure 6* - *Figure 9.*

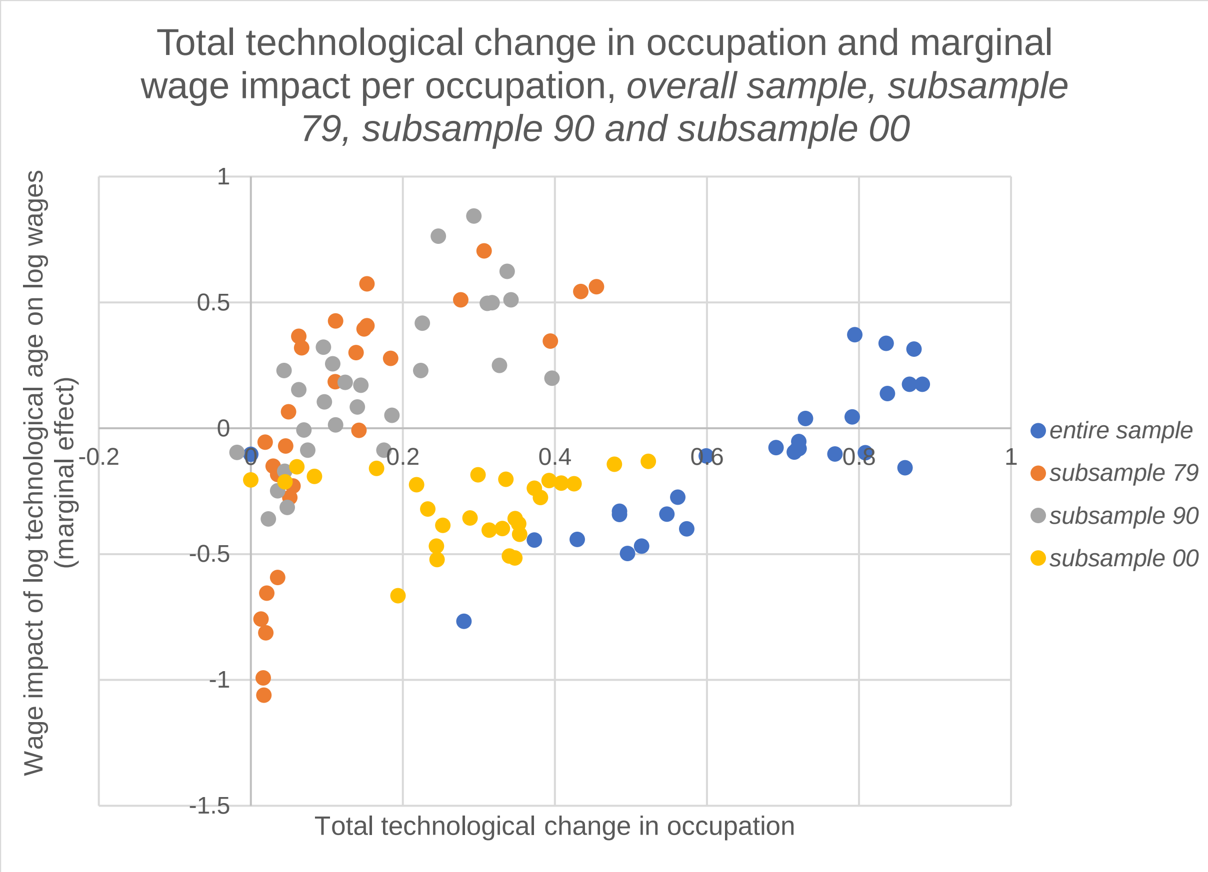

Figure 16: *Total technological change in occupation and marginal wage impact per occupation, overall sample, subsample 79, subsample 90 and subsample 00*

Note: *Marginal effects of regressions (1)-(4) and overall technological change per occupation in each timeframe according to Table A3* to *Table A6.*

Table 13: *Linear correlation between the marginal effects of regressions (1)-(4) and technological change per occupation in each timeframe*

Correlation between	Sample Period	Correlation
marginal effects wage impact	*overall sample*	0.8968
technological change	*overall sample*	
marginal effects wage impact	*subsample 79*	0.6783
technological change	*subsample 79*	
marginal effects wage impact	*subsample 90*	0.7232
technological change	*subsample 90*	
marginal effects wage impact	*subsample 00*	0.0595
technological change	*subsample 00*	

Note: The correlation does not include the observation for woodworking (6).

Figure 16 confirms this suspicion. If anything, the occupations with a medium amount of technological change in *subsample 00* show the largest negative impact of log technological age on log wages as evident by the number of yellow observations in *Figure 16* in the medium range of technological change. The order of marginal effects in *Figure 15* might have been similar, but it seems that the occupations that have not experienced a large degree of technological change across the *overall sample* did experience a large amount of technological change in *subsample 00*. Overall, it seems that occupations in *subsample 00* that experienced either an extremely large amount of technological change or an extremely small amount of technological change also experienced a less negative impact of technological age on wages compared to the occupations with a medium amount of technological change. As *Table 13* shows, the correlation between the impact of log technological age on log wage per occupation and total technological change per occupation was 0.8968 for the *overall sample*, while it was only 0.0595 for *subsample 00*. This further lends credence to the fact that the effect of log technological age on log wages is not linked to the overall experienced technological change per occupation in the *subsample 00*.

Furthermore, in *subsample 79*, the occupations with almost no technological change were the ones to have the largest negative wage impact due to technological age. The more technological change an occupation has experienced, the more positive the wage impact of technological age is. However, there seems to be no linear relationship but rather almost a log distribution. The linear correlation between the impact of log technological age on log wage per occupation and total technological change per occupation is 0.6783. The relationship between the impact of log technological age on log wages and total technological change per occupation is positive linear for *subsample 90*. Alas, the spread of observations is far wider and most of the observations are positive with a correlation of 0.7232.

To sum up, the effects of log technological age on log wages vary across the three different time periods. In the first two time periods, *subsample 79* and *subsample 90*, the effects of log technological age on log wages are generally more positive and somewhat consistent with the overall finding that more technological change in an occupation leads to a less negative impact of log technological age on log wages. However, in *subsample 00*, all occupations show a negative impact of log technological age on log wages. Furthermore, the thus far established correlation between occupations experiencing more technological change also having a more positive impact of log technological age on log wages does not hold true any longer in *subsample 00*. The true effect of technological age on wages is thus still unclear. There seems to be a negative effect of technological age on wages of some kind, in line with Hypothesis 2, especially in recent years. In addition, the observation that more technological change might lessen the negative impact of technological age on wages at some point does not seem to hold. It is furthermore still not clear if the actual impact of technological age is not miss estimated as the possibility that worker could also change occupations due to technological age is still not assessed. The impact of technological age on workers changing occupations is discussed in Section *8*.

The next sections employ another system of classifying occupations, which is the *KldB2010*. First, some more information on the *KldB2010* is given, and then the regressions (1) – (4) are run again as robustness checks employing the *KldB2010* classification. The next section re-estimates regression (1) utilizing the *KldB2010* classification, while Section *7.2* then estimates regressions (2) – (4) employing the *KldB2010* classification.

7 Robustness checks wage analysis

7.1 Regression *overall sample* using *KldB2010*

The reasoning behind utilizing the *KldB88* occupation classification rather than the *KldB2010* classification has been discussed in Section *5.1.2*[55], namely that most of the technological change data is recorded in *KldB88* and transposing the data from *KldB88* to *KldB2010* poses the risk of misidentifying numerous occupations. However, much of the findings might depend on the occupation classification, as the occupations are the basis for the technological change calculations and the marginal effects of log technological age are reported for each occupation. In order to test whether the used classification of occupation has a large impact on the results and the way the results are interpreted, the analysis from Sections *6.1* to *6.4* is repeated using the *KldB2010* occupation classification. Other than the number and naming of occupations, nothing changes in the regression approaches[56]. This section recreates regression (1) using *KldB2010* instead of *KldB88* and reports and analyzes the results. As the *KldB2010* features 36 2-digit occupation classifications compared to the 28 of the *KldB88* and the *KldB2010* regressions are conducted for robustness purposes only, the regression outputs can be found in Appendix A13.i. This section reports the two established graphs of reporting the occupation specific marginal effects, ordering the marginal effects of log technological age on log wages in increasing order per occupation, *Figure 17*, and the graph showing the total technological change per occupation in the x-axis and the marginal effects per occupation on the y-axis, *Figure 18*. Furthermore, the linear correlation between the marginal effects of log technological age on log wages and the total technological change per occupation is reported in *Table 14*. This should give insight into the similarities and differences of the influence of technological age on wages when using the *KldB2010* compared to the *KldB88* occupation classifications.

Figure 17 shows the marginal effects of the impact of log technological age on log wages per occupation. The marginal effects are ordered in size along the x-axis. 14 of the 36 occupations show a positive influence of log technological age on log

[55] More information on the *KldB2010* classification, the occupations and technological change progression can be found in Appendix *A3* and Appendix *A5*.
[56] The explanatory statistics for the *KldB2010* wage analysis can be found in Appendix *A9*.

wages, amounting to about 39 percent of the total occupations. All marginal effects except entertainment (94) are statistically significant. What immediately comes to mind is that the range of the marginal effects is very similar using *KldB2010* when compared to *KldB88*. When using the *KldB88*, the occupation with the largest negative marginal effect was construction (13) with -0.7675. When using *KldB2010*, the occupation with the largest negative marginal effect is still construction (32) with -0.7567. Furthermore, the fact that in both settings technological age in the construction sector seems to have the largest negative impact points towards further similarities between the regressions. The occupations with the largest positive marginal effect when using *KldB88* was service_merchants (22) with 0.3709. When using *KldB2010* the occupation with the largest positive marginal effect is IT (43) with 0.5008. While the *KldB88* does not have a classified IT occupation, the range of the marginal effects is very similar, nonetheless. Finally, it also seems like the kind of occupations that showed a positive marginal effect in regression (1) also show a positive marginal effect when using *KldB2010*, the same being true for negative marginal effects. The occupations at the positive end of the distribution of marginal effects are IT (43), finance (72), social_science (91), marketing (92) and electrical_engineer (26). These are all technologically intensive, high educated and paying occupations, similar to the occupations with positive marginal effects in regression (1). Contrary, the occupations with the most negative marginal effects pf log technological age on log wages are construction (32), drivers (52), wellness (82), cleaning_service (54) and interior_construction (33). These occupations probably experienced a lot less technological change across the time period. The overall trend of low technology intensive occupations being hurt more by technological age compared to highly technologically intensive occupations seems to hold true when using the *KldB2010*.

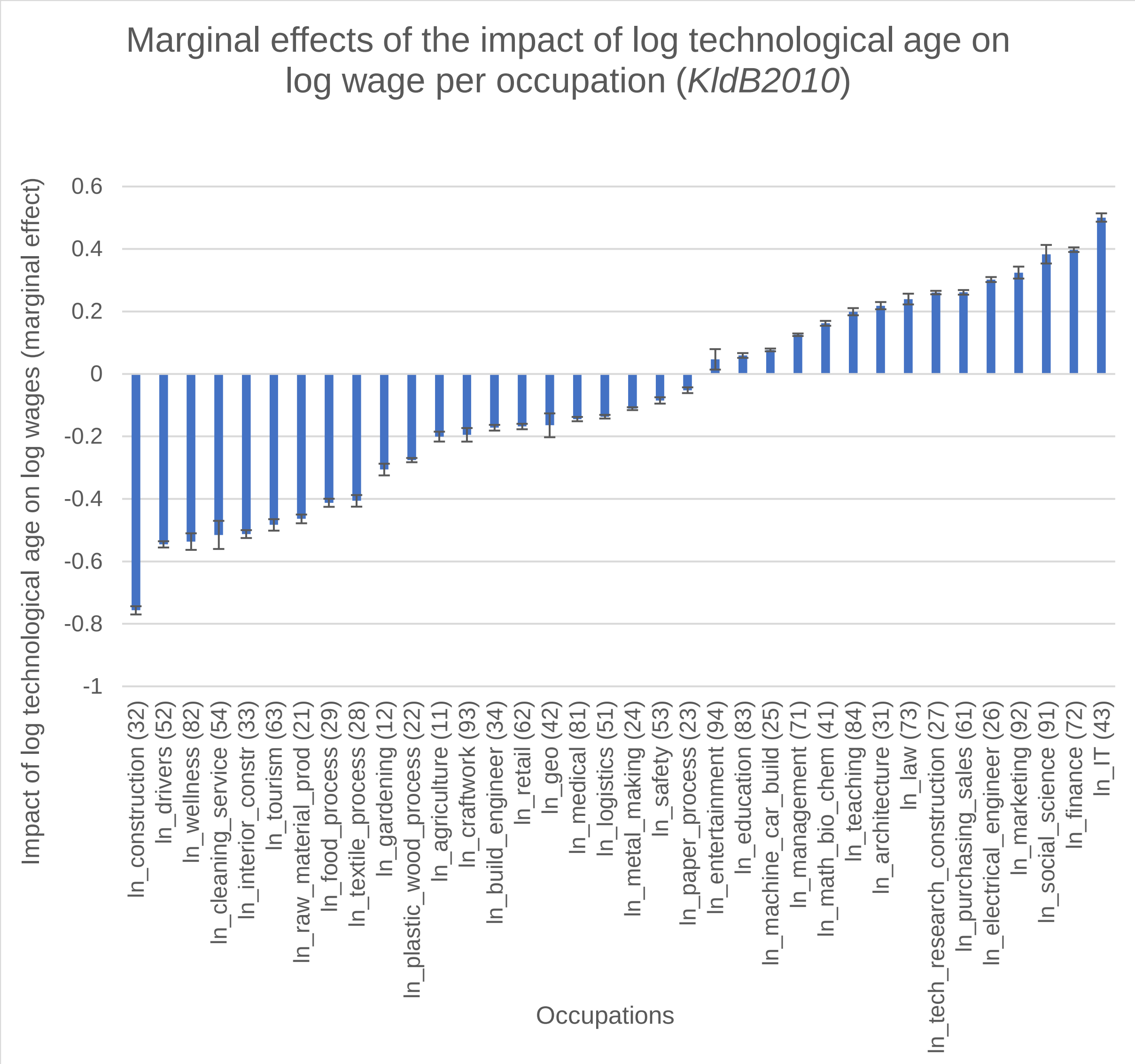

Figure 17: *Marginal effects of the impact of log technological age on log wage per occupation (KldB2010)*

Note: Marginal effects of regression (10) ordered by size. Including standard errors. Regression (10) can be found in Table A54.

Figure 18 confirms this suspicion. While *Figure 18* is a bit more spread out than *Figure 12*, a clear positive linear trend is obvious. There are two outliers visible in *Figure 18*; the very positive data point on the left is the coefficient for IT (43). As the IT occupation already had a large share of computer users in 1979 when the sampling period started, the total change in overall computer usage was minimal throughout the whole time period until 2006. However, it would be presumptuous to think that technological change has not impacted the IT profession in the last 30 years. This result is thus simply due to the way technological change is measured in only computer usage while actual technology progression might encompass many more facets[57]. The other outlier with minimal technological change is the occupation cleaning_service (54). In this case, it is not as obvious as to why there is so little technological change measured for this occupation, the measured technological change might be accurate. However, the impact of log technological age on log wage is not as negative as expected. When excluding the IT (43) occupations, the correlation between the impact of log technological age on log wages per occupation and the total technological change per occupation amounts to 0.8051, as can be seen in *Table 14*. While *Figure 18* is a bit more scattered than *Figure 12*, this correlation is very comparable to the correlation of regression (1) and total technological change per occupation in *Table 11* using *KldB88* amounting to 0.8968.

Overall, the results using the *KldB2010* occupation classification when compared to using the *KldB88* occupation classification are very similar. Not only is the range of the marginal effects comparable, the distribution and the kind of occupations with positive and negative marginal effects are also very similar. Furthermore, the distribution when comparing marginal effects and total technological change are both positive and linear. Overall, it seems that changing the occupation classification hardly changes the overall results or their interpretation. In order to further test this finding, the next section also uses split time samples as in Section *6.4*, and tests whether the trends of *subsample 79, subsample 90* and especially *subsample 00* are also unaffected by changing the occupation classifications.

[57] Some of this comes back to the problems with measuring technological change as discussed in Section *4.1* and is addressed again in Section *11.1 The measurement of technological change*.

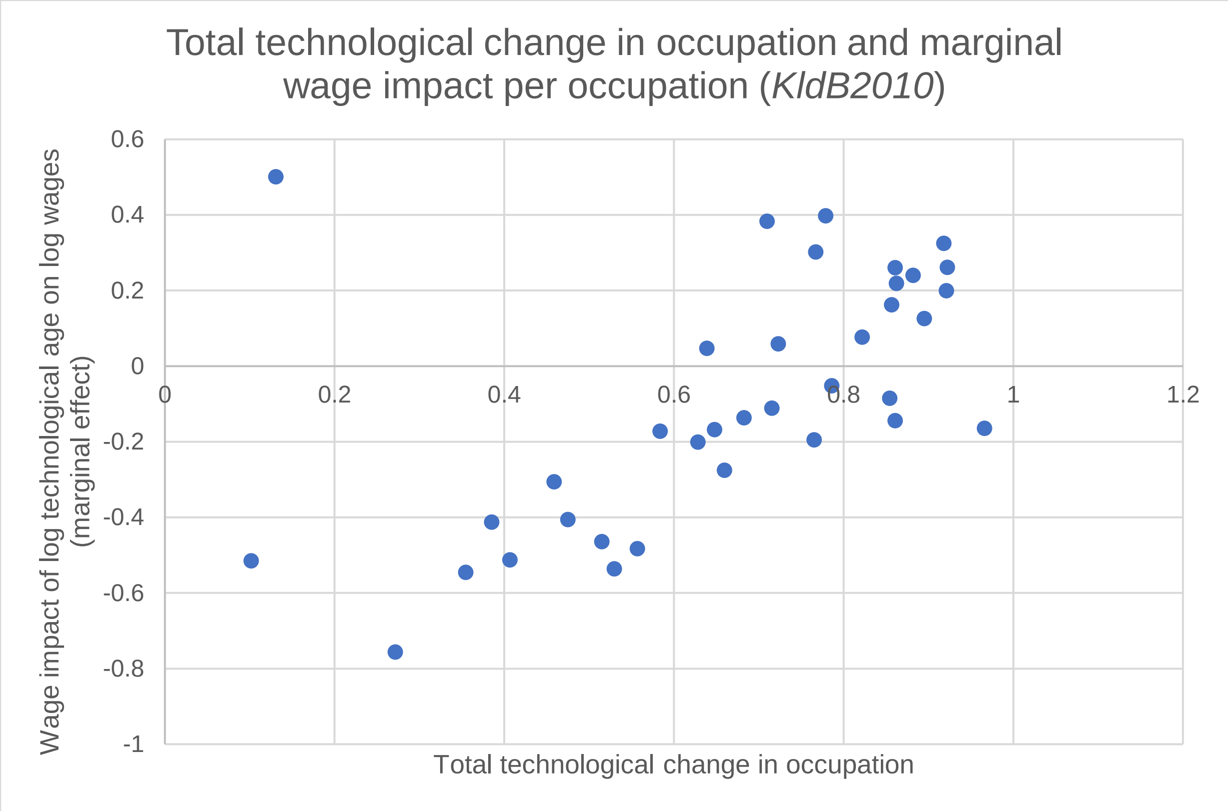

Figure 18: *Total technological change in occupation and marginal wage impact per occupation (KldB2010)*

Note: Marginal effects of regression (10) and overall technological change per occupation from Table A11 to Table A15. Regression (10) can be found in *Table A54*.

Table 14: *Linear correlation between the marginal effects of regression (10) and technological change per occupation*

Correlation between	**Sample Period**	**Correlation**
marginal effects wage impact (*KldB2010)*	*overall sample*	0.8968
technological change *(KldB2010)*	*overall sample*	

Note: The correlation does not include the observation for IT (43).

7.2 Regressions *subsample 79, subsample 90* and *subsample 00* using *KldB2010*

Following the same logic as Section *6.4 Regression discussion subsample 79, subsample 90 and subsample 00*, the regression utilizing the *KldB2010* is also split into the same three subsample periods *subsample 79, subsample 90* and *subsample 00*. However, as in Section *7.1*, the results are only reported in graphical form here and the full regression outputs can be found in Appendix *A13.ii*. The graphs used are the same as in the previous sections, one graph showing the occupation specific marginal effects of log technological age on log wages and one graph plotting the occupation specific marginal effects of log technological age on log wages and the total amount of technological change per occupation. *Figure 19* - *Figure 21* depict the marginal effects of the impact of log technological age on log wages for *subsample 79, subsample 90* and *subsample 00* respectively. As before, the marginal effects are shown on the y-axis and are ordered by size along the x-axis. For reference, the marginal effects of regression (10) depicted in *Figure 17,* using the *overall sample*, are included in each figure again. Finally,

Figure 22 shows the marginal effects of all three time period splits and the marginal effects of the *overall sample* on the y-axis and the total technological change experienced per occupation on the x-axis. The linear correlation between the marginal effects and the total technological change per sample period are displayed in *Table 15*.

Figure 19 shows the marginal effects of the impact of log technological age on log wages during *subsample 79* and the *overall sample* utilizing the *KldB2010* classification. Similar to regression (2) using the *KldB88* classification during *subsample 79*[58], there are overall more positive marginal effects of log technological age on log wages compared to the *overall sample*. Especially the size of the positive marginal effects is much larger compared to the *overall sample*, in *Figure 19* even more so than in *Figure 13: Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 79*. Generally, it can be said that the occupations with a positive marginal effect of log technological age on log wages across the *overall*

[58] For reference, see *Figure 13: Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 79*.

sample also show a positive marginal effect in *subsample 79*. Furthermore, the negative marginal effects are situated towards the left-hand side of the graph, showing that the distribution of marginal effects is somewhat similar between the two regressions, with the *subsample 79* regression having larger and more positive effects. Overall, the comparison between the *KldB2010* and the *KldB88* regressions of *subsample 79* and the *overall sample* are very similar.

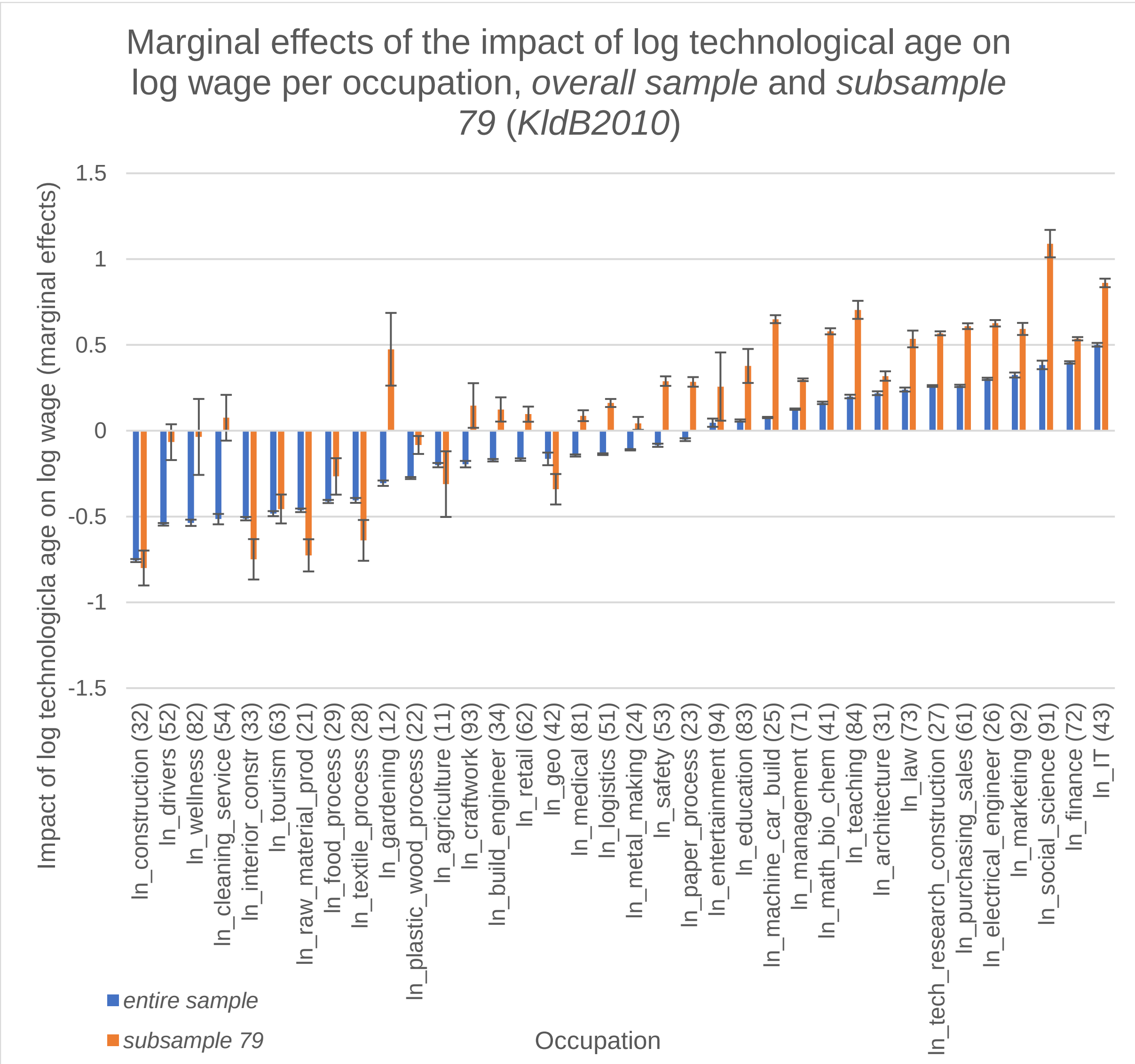

***Figure 19:** Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 79 (KldB2010)*

Note: Marginal effects of regression (10) and regression (11), ordered by size of marginal effects in regression (10) including standard errors. Regression (10) and (11) can be found in Table A55.

Figure 20 shows the marginal effects of the impact of log technological age on log wages across the *overall sample* and during *subsample 90* using the *KldB2010* occupation classification. *Figure 20* is similar to *Figure 14: Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 90,* in the sense that almost no negative marginal effects exist in the *subsample 90* and the positive marginal effects increased dramatically in size when compared to the marginal effects of the *overall sample*. Furthermore, the largest positive marginal effects are on the right-hand side in *Figure 20* and *Figure 14* indicating that at least some of the positive marginal effects of log technological change on log wages in the *overall sample* stems from the *subsample 90*. The regressions of *subsample 90* using the *KldB88* and *KldB2010* occupation classifications are quite similar overall indicating that changing occupation classifications does not make a large difference is this case.

Figure 21, depicting the marginal effects of log technological age on log wages across the *overall sample* and *subsample 00* using the *KldB2010* occupation classifications is also very similar to *Figure 15: Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 00*. All marginal effects from *subsample 00* are either negative or insignificant while the occupations on the left-hand side have a generally more negative marginal effect attached than the ones on the right-hand side. Furthermore, the marginal effects of log technological age per occupation during *subsample 00* on the left-hand side are very close in size to the marginal effects of log technological age during the *overall sample* on the left-hand size. This is also similar to the corresponding *Figure 15*. Changing occupation classifications does not seem to change much in *subsample 00* either.

Overall, the largest difference between the regressions using the *KldB88* and *KldB2010* can be found for *subsample 79*, and even then, the differences are not very large. For the other two subsamples, the results are very similar indeed. This similarity continues when looking at the impact of log technological age on log wages in relation to overall experienced technological change per occupation.

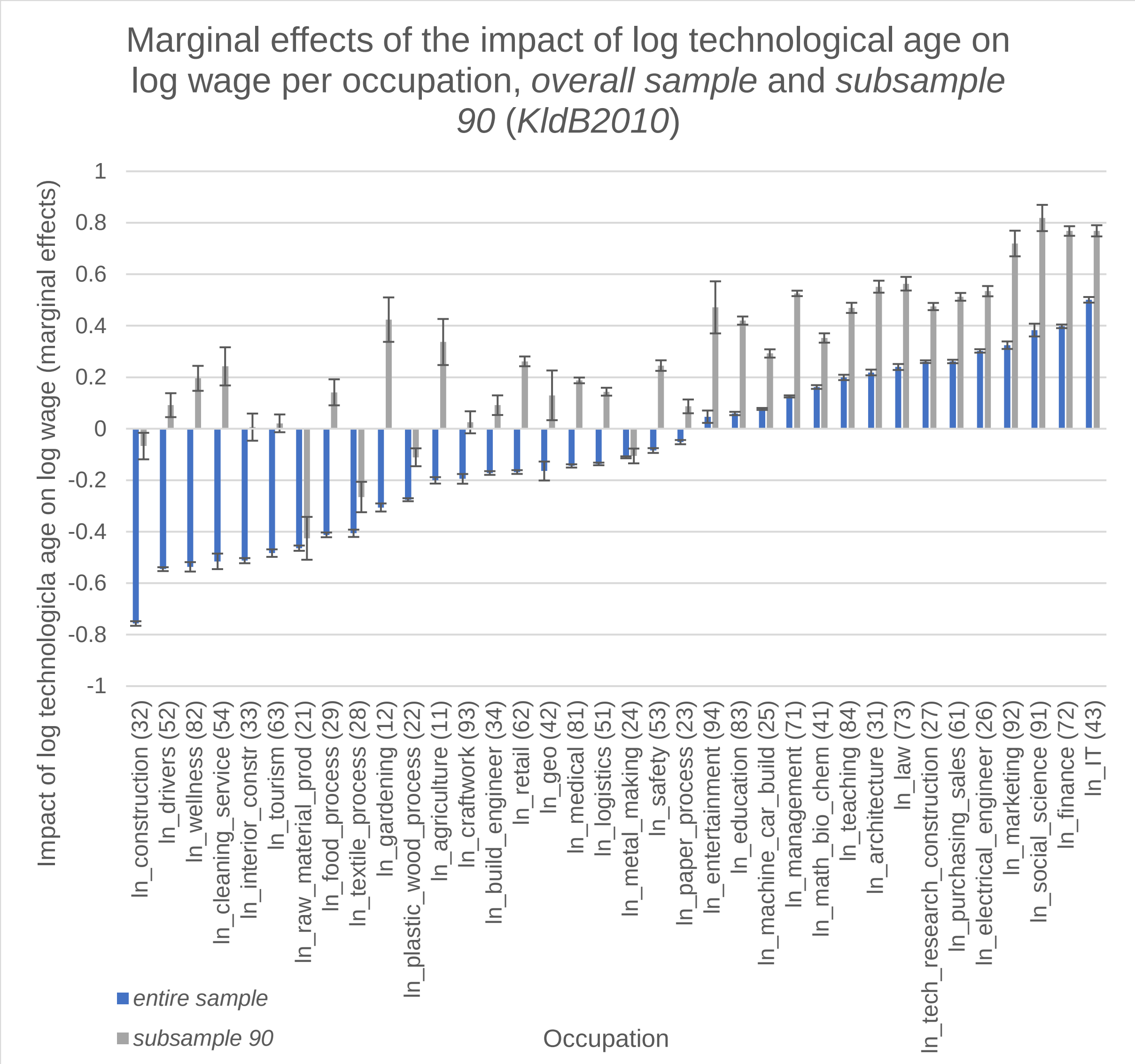

Figure 20: *Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 90 (KldB2010)*

Note: Marginal effects of regression (10) and regression (12), ordered by size of marginal effects in regression (10) including standard errors. Regression (10) and (12) can be found in Table A55.

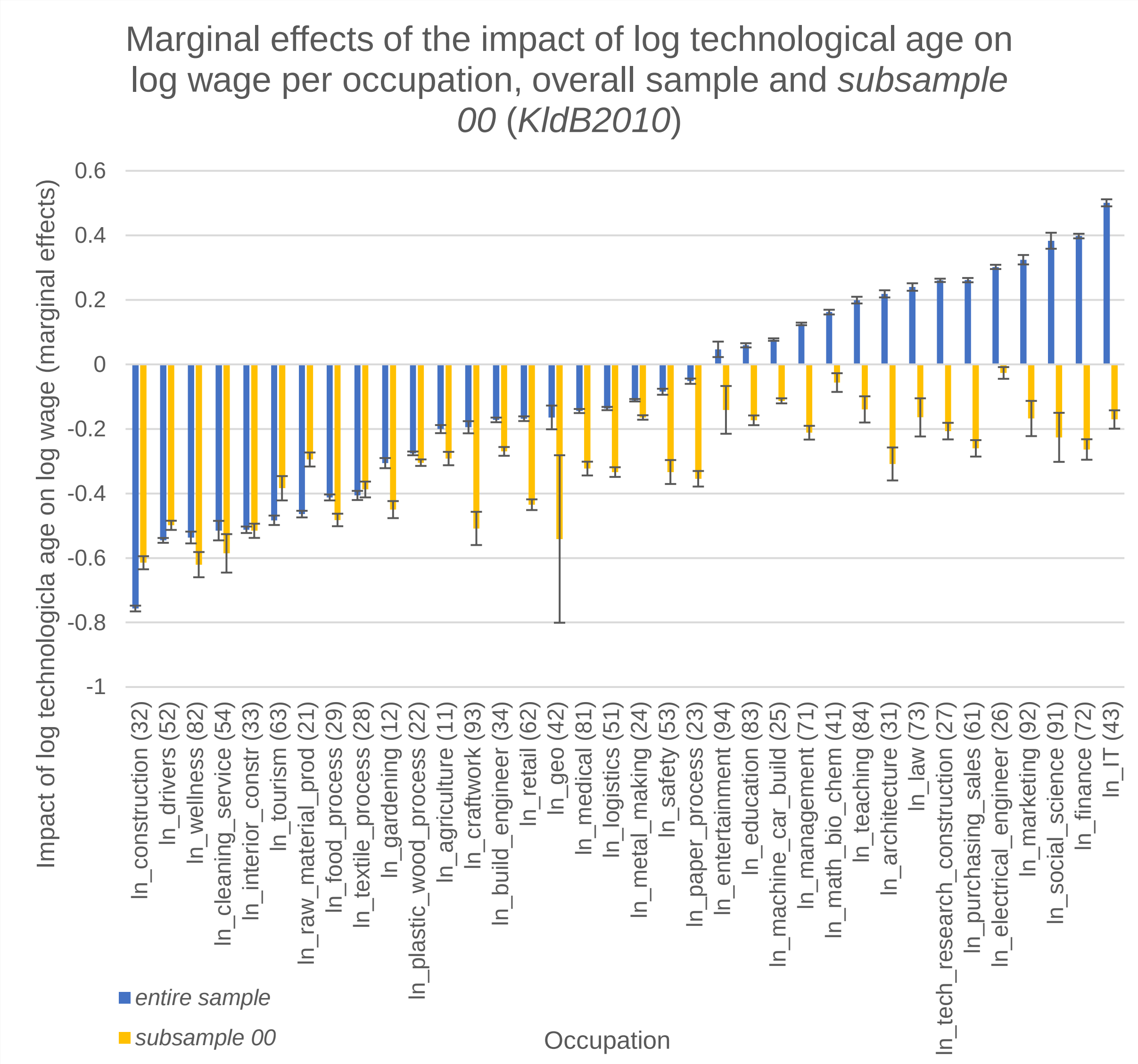

Figure 21: *Marginal effects of the impact of log technological age on log wage per occupation, overall sample and subsample 00 (KldB2010)*

Note: Marginal effects of regression (10) and regression (13), ordered by size of marginal effects in regression (10) including standard errors. Regression (10) and (13) can be found in Table A55.

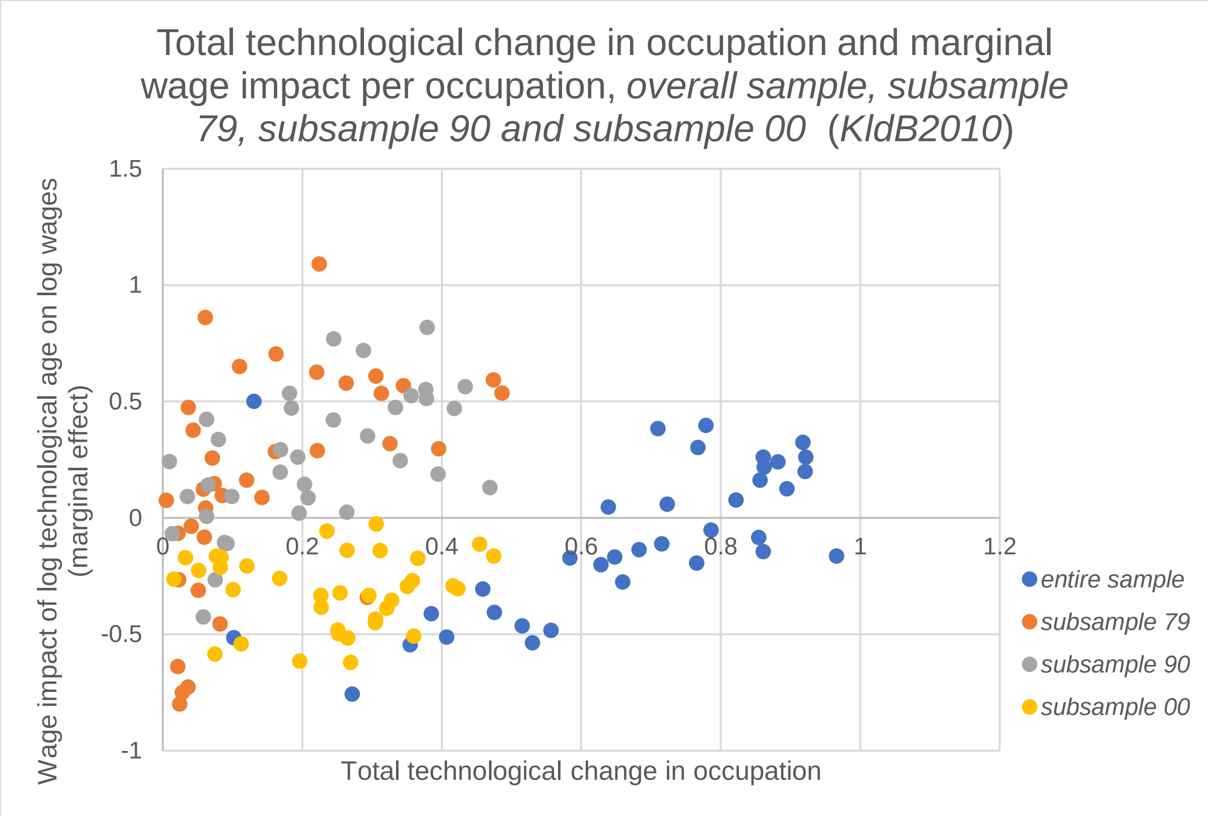

Figure 22: *Total technological change in occupation and marginal wage impact per occupation, overall sample, subsample 79, subsample 90 and subsample 00 (KldB2010)*

Note: Marginal effects of regressions (10)-(13) and overall technological change per occupation from Table A11 to Table A15 in each timeframe. Regression (10)-(13) can be found in *Table A55*.

Table 15: *Linear correlation between the marginal effects of regressions (10)-(13) and technological change per occupation in each timeframe*

Correlation between	Sample Period	Correlation
marginal effects wage impact *(KldB2010)* technological change *(KldB2010)*	*overall sample* *overall sample*	0.8051
marginal effects wage impact *(KldB2010)* technological change *(KldB2010)*	*subsample 79* *subsample 79*	0.5658
marginal effects wage impact *(KldB2010)* technological change *(KldB2010)*	*subsample 90* *subsample 90*	0.5712
marginal effects wage impact *(KldB2010)* technological change *(KldB2010)*	*subsample 00* *subsample 00*	0.0837

Note: The correlation does not include the observation for IT (43).

As before, *Figure 22* plots the marginal effects of technological age per occupation and the total technological change per occupation for regressions (10) - (13), utilizing the *KldB2010* occupation classifications, while *Table 15* shows their linear correlation. Even though it is already established that the relation between the marginal effects of log technological age per occupation on log wages and total technological change per occupation of the *overall sample* is similar between the regressions using *KldB88* and *KldB2010*[59], the same can also be said for the regressions of *subsample 00*[60]. The *KldB2010* results for *subsample 00* are a little bit more skewed towards the left-hand side, meaning that there are a few more occupations that experienced almost no technological change during *subsample 00* that have a larger negative impact of log technological age on log wage. However, the difference is rather minor. For comparison, the correlations between the impact of log technological age on log wages per occupation and the total technological change per occupation for *subsample 00* using *KdlB88* yields 0.0595[61]. Using *KldB2010* the correlation is 0.0837 as *Table 15* shows, which is similar. When looking at the distribution of the plot of *subsample 90*, it is obvious that the spread of results along the y-axis is even greater for the *KldB2010* regression, so much so that it is almost impossible to make out a distribution easily. The correlation between the marginal effects of log technological age on log wages and total technological change is 0.5712 using the *KldB2010* regression results compared to the 0.7232 of the *KldB88* regression results. The plot for the *subsample 79 KldB2010* regression is also much more spread out than the plot for *subsample 79 KldB88* regression, yet at least a similar distribution of the *KldB2010* plot compared to the almost clear log distribution of the *KldB88* plot can be seen. The comparison of the correlation of the impact of log technological age on log wages per occupation and the total technological change per occupation is 0.6783 for the *KldB88* results compared to the 0.5658 of the *KldB2010* results.

Overall, the results of the regressions when using *KldB88* compared to *KldB2010* are rather similar. Not only are the results of similar size and also similar

[59] For reference see *Figure 12: Total technological change in occupation and marginal wage impact per occupation* and *Figure 18: Total technological change in occupation and marginal wage impact per occupation (KldB2010).*

[60] For reference see *Figure 16: Total technological change in occupation and marginal wage impact per occupation, overall sample, subsample 79, subsample 90 and subsample 00* and *Figure 22: Total technological change in occupation and marginal wage impact per occupation, overall sample, subsample 79, subsample 90 and subsample 00 (KldB2010).*

[61] For reference see *Table 13: Linear correlation between the marginal effects of regressions (1)-(4) and technological change per occupation in each timeframe.*

range, the results also have a similar correlation between the impact of log technological age on log wages per occupation and the total amount of technological change experienced per occupation in time period. The largest difference in marginal effects can be found in the *subsample 79* regression while the largest difference in correlation between the impact of log technological age on log wages and overall technological change can be found in *subsample 90*. The *subsample 00* regressions and the *overall sample* distribution are overall very similar. The trend that the more technological change an occupation has experienced, the less negative the wage impact of technological age, is a bit smaller using *KldB2010*, yet the overall trend for the different timeframes is similar. The results from Section *6.4* thus also hold up when changing occupation classification from *KldB88* to *KldB2010*. The next session discusses other possible robustness checks such as adding age squared to the regression or lagging technological age.

7.3 Further robustness checks

This section shorty discusses other possibilities of testing for robustness, such as extending the sample period with the use of the *KldB2010* occupation classifications, imputing starting technology or lagging technological age.

A first possibility when checking for robustness could be extending the sample period until 2012. Due to the *KldB2010* occupation classification being included in one more wave of the *BIBB Data* (the last wave is 2012), it is possible to extend the *overall sample* six more years. As the robustness checks before already established that the results between using the *KldB88* and the *KldB2010* occupation classifications are not much different from one another, it might be interesting to see whether the results are also robust for further years. It would be especially interesting, as the *subsample 00* regression, regression (4), suggests that in the last years of the sample period the impact of log technological age on log wages is much more negative than before. However, the difference in the marginal effects of the impact of log technological age on log wages is minimal across the entire sample when comparing the regression using the *overall sample* and the timeframe 1979-2012. A comparison of the results can be found in Appendix *A13.iii*.

Furthermore, it would be possible to impute the starting technological age for everyone starting to work before the start of the dataset in 1979. There are several problems with assuming the starting technological age in the data[62], one of them being the assumption that if a person starts to work before the starting date of the sample period, the starting technological age is simply the starting technological age in 1979. As there is no data on computer usage before 1979 and most occupations only have very low levels of used technology, however, this should not be a large problem. Nonetheless, it would be possible to simply assume a linear trend in technological change between 1979 and 1986 and calculate it backwards so that the levels of technology before 1979 for each occupation can be added into the data. Alas, adding technology data for working starts before 1979 also does not have a large impact on the results, as can be seen in Appendix *A13.iv*. This does of course make sense as the fixed effects regression uses within variation to estimate the effects of log technological age on log wages and the yearly change in technological age in each occupation in the sample period is unaffected by the starting technology. Overall, the results of regression (1) and regressions (2) - (4) seem to be rather robust and the measured impact of log technological age on log wages does not change much with the used robustness checks.

Finally, it would be possible to lag the technological age variable. Alas, lagging technological age by one year only changes the size of the marginal effects slightly, as shown in Appendix *A13.v*. This is also not surprising as the fixed effects regression only captures the yearly change in technological age, which does not vary much from year to year. In fact, due to the assumption of linear technological change between the measured waves[63], lagging the technological age variable has almost no impact on the data.

The next section addresses another approach to measuring the influence of technological age entirely. It is dedicated to finding whether technological age makes workers more likely to change occupations in line with Hypothesis 3. This in turn would

[62] See Section *4.2 Regression model wage analysis* and Section *5.2.1 Data description SIAB Data*.
[63] See Section *5.1.1 Measuring technological change* and Section *5.1.4 Technological progression according to BIBB Data.*

then also be telling for the analysis of the impact of log technological age on log wages as workers who change their occupation might also do so in order to escape wage penalties or to preempt them. Generally, the analysis of the impact of technological age on occupation change behavior is structured similarly to the analysis of the impact of technological age on wages. First, there is a regression using the *overall sample*. Then, the sample period is split into the three timeframes and the regressions are repeated for each subsample. Lastly, *KldB2010* is be used as a robustness check with further robustness checks following.

8 Occupation change analysis

Until now, the regression analyses in Section *6* and Section *7* have been focused on the influence of technological age on wages, testing Hypothesis 2. Hypothesis 2 seems to be true for many occupations across the entire sample period, for the last few years Hypothesis 2 seems to be true for all occupations. Alas, there are other ways technological age could affect workers and only looking at wages might leave out an important aspect. There is no reason that workers should simply stay in their occupations if they receive wage penalties when their technological age increases. Technological age could therefore push workers to change occupations, leading to Hypothesis 3, that technological age makes workers more likely to change occupations. The regression functions described in Section *4.3* are employed to test Hypothesis 3 and analyze whether technological age makes workers more likely to leave their occupation. In order to do so, the occupation change analysis is structured similarly to the wage analysis in Section *6* and Section *7*.

The occupation change analysis section covers the results and discussion of how technological age affects workers' likelihood to leave their occupation utilizing the regression function described in Section *4.3*. The regressions are in the same order as in the wage analysis; first, the regression results of the *overall sample* are reported and discussed, showing how technological age impacted the likelihood of workers leaving their occupations across the *overall sample* period. In order to check for a differing impact of technological age in different time periods, the regression is estimated again for the three subsample time periods of *subsample 79, subsample 90* and *subsample 00.* The results of the subsample regressions are then reported and discussed.

Similar to the wage analysis, the occupation change analysis only employs regressions estimating the impact of technological age on workers' likelihood to leave an occupation on an occupational level. Naturally, technological age should affect different occupations in different ways as discussed in Sections *3* and *4.1*. Yet, in reference to the literature looking at the retirement decisions of older workers[64], as well as the literature looking at the labor demand of innovative firms of older workers[65] without

[64] For example, Ahituv and Zeira (2011), Bartel and Sicherman (1993), Friedberg (2003) are looking at the retirement decisions of older workers.
[65] This literature includes for example Aubert, Caroli and Roger (2006), Abowd et. al. (2007), Beckmann (2007), Behaghel, Caroli, and Roger (2014) and Schleife (2008).

strictly imposing occupational effects, Appendix *A14.i* shows the regression results for a non-occupation specific effect of technological age on the likelihood of workers leaving their occupations. The regression in Appendix *A14.i* estimates the impact θ of technological age regardless of occupation j. From here on, this thesis shows the impact of technological age on the likelihood of workers leaving their occupations on an occupational level. The next section therefore reports the regression results for regression function *(7)*, using the *overall sample*.

8.1 Regression results *overall sample*

This section covers the report of the first regression estimating the impact of technological age on the likelihood to leave and occupation, covering the *overall sample* of 1979-2006. The marginal effects of technological age for each occupation can be found in *Table 16: Regression (5), the impact of technological age on the likelihood to change occupations, overall sample,* while the full regression output can be found in *Table A60* in Appendix *A14.ii.* The first thing to note is that regression (5) utilizes 11,030,551 observations and reaches an adjusted R-squared of 0.0515. All coefficients are highly significant[66], except for the coefficient for the occupation service_merchants (22) which is significant at the five percent level and the coefficients for occupations agriculture_fishing (1), woodworking (6), and machinist (18) which are insignificant. The largest negative coefficient in regression (5) is the coefficient of the product_testing (17) occupation with -0.0989, while the construction (13) occupation has the largest positive coefficient with 0.2608. The coefficient for the construction (13) occupation is much larger than the next largest significant coefficient of the textile_clothing_fur (11) occupation with 0.1171.

Since regression (5) is based on a linear probability model, an increase in technological age by one leads to a percent increase or decrease in the likelihood of a

[66] The following occupations have a significant coefficient at least at the one percent level: miners_stone_workers (2), ceramic_glas (3), chemistry_synthetic_workers (4), paper_print (5), metal_works (7), mechanics (8), electricians (9), assembly (10), textile_clothing_leather_fur (11), food (12), construction (13), interior_construction (14), carpenter (15), painter (16), product_testing (17), engineer_math_chem (19), technical_specilaist (20), goods_merchants (21), service_merchants (22), traffic (23) administration (24), regulatory_safety (25), writing_art (26), healthcare (27) and social_education_science (28).

worker leaving each occupation. For example, an increase in technological age by one would make an employee in the miners_stone_worker (2) occupation 8.79 percent more likely to change occupations as can be seen in *Table 16*. Alas, an increase in technological age by one would mean that at the point of entry into the labor market, no one used computers and now everyone in the occupation uses computers. This means that an increase in technological age by one is very unlikely in most occupations and for all the workers entering the labor market where computers already exist an increase of one is impossible. However, since technological age is measured in percent computer users on a scale from zero to one, an increase in technological age by one percentage point would make an employee in the miners_stone_worker (2) occupation 0.08 percent more likely to change occupations. Generally, only interpretations to the changes at the one percentage point level make sense as this represents a one-unit increase in technological age.

Considering that all but three occupation specific coefficients of technological age are significant, it can be said that technological age indeed has an impact on the probability to leave ones' occupation. However, Hypothesis 3 is again not entirely proven. In nine out of twenty-eight occupations[67] (or about 32 percent), technological age decreases the probability of a worker leaving ones' occupation. While for some occupations this probability is very small (metal_works (7) -0.0138 or service_merchants (22) -0.0063) the effect is not positive. Thus, technological age does not make workers in these occupations more likely to leave. As before, it is very difficult to explain why this might be the case. It is possible that workers in these occupations are trained very specially and narrowly so that they cannot easily change occupations. However, as the analysis does not provide a sound reasoning, any attempts to explain this phenomenon would be pure speculation.

Something to keep in mind is that the occupations where technological age has a negative impact on changing occupations are not the same occupations where technological age has a positive impact on wages, with the exception of the service_merchants (22) occupation. Section *10* discusses the results of both, the wage and the occupation change approach together and draws more joint conclusions there.

[67] The following occupations have a negative coefficient: ceramic_glas (3), chemistry_synthetic_workers (4), paper_print (5), metal_works (7), assembly (10), product_testing (17), service_merchants (22), traffic (23) and regulatory_safety (25).

The remaining 12 significant occupations[68] (about 57 percent of the total occupations) show a significant positive impact of technological age on the probability to change occupation. Thus, Hypothesis 3 holds true for these occupations and technological age makes workers more likely to leave in these occupations. While regression (5) does not make it possible to say whether workers leave to avoid the wage penalty of technological age, whether they cannot keep up with technological change any longer and leave of their own volition or whether they are forced to leave, it is clear that technological age also influences the occupation a worker is employed in. In some occupations[69], this effect is much larger ranging from 0.0879 for the miners_stone_workers (2) occupation to 0.2608 for the construction occupation. In other occupations[70], the effect ranges from 0.0155 for the goods_merchants (21) occupation to 0.0598 for the electricians (9). Overall, it must be kept in mind that the coefficients in this analysis are not extremely large. When for example a carpenter (15) increases his/her technological age by one percentage point (or by 0.01), it is only about point zero one percent (0.0098) more likely that he/she will leave their occupation. For many occupations this likelihood is even smaller. Furthermore, it must be kept in mind that each occupation has a maximum amount of technological age that is possible to reach over the timeframe. Some occupations do not experience a large amount of technological change, which in turn means that the maximum technological age possible to experience in said occupation is capped at the amount of technological change that happened in the occupation. This in turn limits the range of interpretation of the marginal effects of these occupations. If the maximum amount of technological age in an occupation can only be 0.5, any interpretation of the coefficients for an increase in technological age larger than 0.5 cannot be made. Alas, while the interpretation of the marginal effects at the one percentage point level of technological age change is possible, for some occupations the maximum interpretation range is capped by the amount of technological age witnessed in that occupation. Additionally, it is important to note that the linear probability model imposes a linear relationship between the increase in

[68] The following occupations have positive significant coefficients: miners_stone_workers (2), mechanics (8), electricians (9), textile_clothing_leather_fur (11), food (12), construction (13), interior_construction (14), carpenter (15), painter (16), engineer_math_chem (19), technical_specilaist (20), goods_merchants (21), administration (24), writing_art (26), healthcare (27) and social_education_science (28)

[69] miners_stone_workers (2), textile_clothing_leather_fur (11), food (12), construction (13), carpenter (15) and painter (16).

[70] mechanics (8), electricians (9), interior_construction (14), engineer_math_chem (19), technical_specilaist (20), goods_merchants (21), administration (24), writing_art (26), healthcare (27) and social_education_science (28).

technological age and the probability to leave an occupation. While this may well be true, it is also a possible limitation, especially for occupations that have experienced a large amount of technological change. However, overall it can be said that technological age does make workers in many occupations more likely to leave and thus influences the occupations some workers are employed in.

Following *Table 16*, the next section employs the graphical presentation of the coefficients of regression (5) that has been used in this thesis so far. First, the coefficients are ordered by size along the x-axis and their marginal effects reported along the y-axis. Afterwards, the total technological age each occupation has experienced is plotted along the x-axis while the coefficients themselves are plotted along the y-axis. These two graphs then again build the foundation for a more in-depth discussion of the results and for further interpretation.

Table 16: *Regression (5), the impact of technological age on the likelihood to change occupations, overall sample*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)
agriculture_fishing (1)	.0068
	(.0061)
miners_stone_workers (2)	0.0879***
	(.0126)
ceramic_glas (3)	-0.0694***
	(.0153)
chemistry_synthetic_workers (4)	-0.0739***
	(.0041)
paper_print (5)	-0.0369***
	(.0054)
woodworking (6)	.1704
	(.1014)
metal_works (7)	-0.0138***
	(.0035)
mechanics (8)	0.0472***
	(.0023)
electricians (9)	0.0598***
	(.0032)
assembly (10)	-0.0591***
	(.0051)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)
textile_clothing_leather_fur (11)	0.1171***
	(.0116)
food (12)	0.0950***
	(.0074)
construction (13)	0.2608***
	(.0088)
interior_construction (14)	0.0506***
	(.0101)
carpenter (15)	0.0980***
	(.0073)
painter (16)	0.1099***
	(.0080)
product_testing (17)	-0.0989***
	(.0057)
machinist (18)	.0104
	(.0060)
engineer_math_chem (19)	0.0247***
	(.0029)
technical_specilaist (20)	0.0418***
	(.0023)
goods_merchants (21)	0.0155***
	(.0029)
service_merchants (22)	-0.0063*
	(.0027)
traffic (23)	-0.0163***
	(.0033)
administration (24)	0.0194***
	(.0016)
regulatory_safety (25)	-0.0561***
	(.0049)
writing_art (26)	0.0255***
	(.0056)
healthcare (27)	0.0520***
	(.0020)
social_education_science (28)	0.0251***
	(.0028)
Constant	0.3665***
	(.0039)
N	11,030,551
R-sq	0.0515

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

8.2 Regression discussion *overall sample*

This section covers the two so far standardly used graphs aiming to give a better understanding of the 28 occupation specific coefficients of the regression. The first graph, *Figure 23*, orders the marginal effects of regression (5) by size along the x-axis and depicts the size of the marginal effects on the y-axis. *Figure 24* then depicts the total amount of technological change each occupation has experienced across the *overall sample* on the x-axis and the likelihood to leave an occupation due to technological age on the y-axis. This graph again makes the relationship between the probability to leave occupation due to technological age and total technological change per occupation clear. *Table 17* provides the linear correlation between the probability to leave an occupation due to technological age and total technological change per occupation to quantify the correlation.

Figure 23, depicting the probability to leave an occupation due to technological age and the standard errors of the marginal effects, paints a clear picture. As stated above, in most occupations technological age has a positive effect on the probability to leave an occupation, yet most effects are rather small (ranging from -0.1 to 0.11). There are also some occupations in which technological age lowers the probability to leave the occupation. Several of the occupations in the middle segment of the distribution have an insignificantly small marginal effect of technological age on the probability to leave the occupation with woodworking (6) being statistically insignificant as well. The occupations where technological age has a negative influence on whether a worker is likely to leave are not the most technologically intensive occupations. The technological change in the ceramic_glas (3), chemistry_synthetic_workers (4), paper_print (5), assembly (10), product_testing (17) and regulatory_safety (25) occupations are more so in the middle of the distribution when it comes to total technological change during the time period, as is evident from *Figure 6* to *Figure 9*. When measuring the impact of technological age on the probability to change occupation, the occupations that have experienced a lot of technological change are the ones who do not show a very large impact at all. Alas, the occupations where technological age increases the likelihood to change occupations the most are again the occupations that have experienced the least overall amount of technological change across the sample period. The miners_stone_workers (2), textile_clothing_leather_fur (11), food (12), construction (13), carpenter (15) and painter (16) occupations are all not technologically intensive. Therefore, the least technologically intensive occupations also show the largest likelihood of workers leaving their occupations due to technological age.

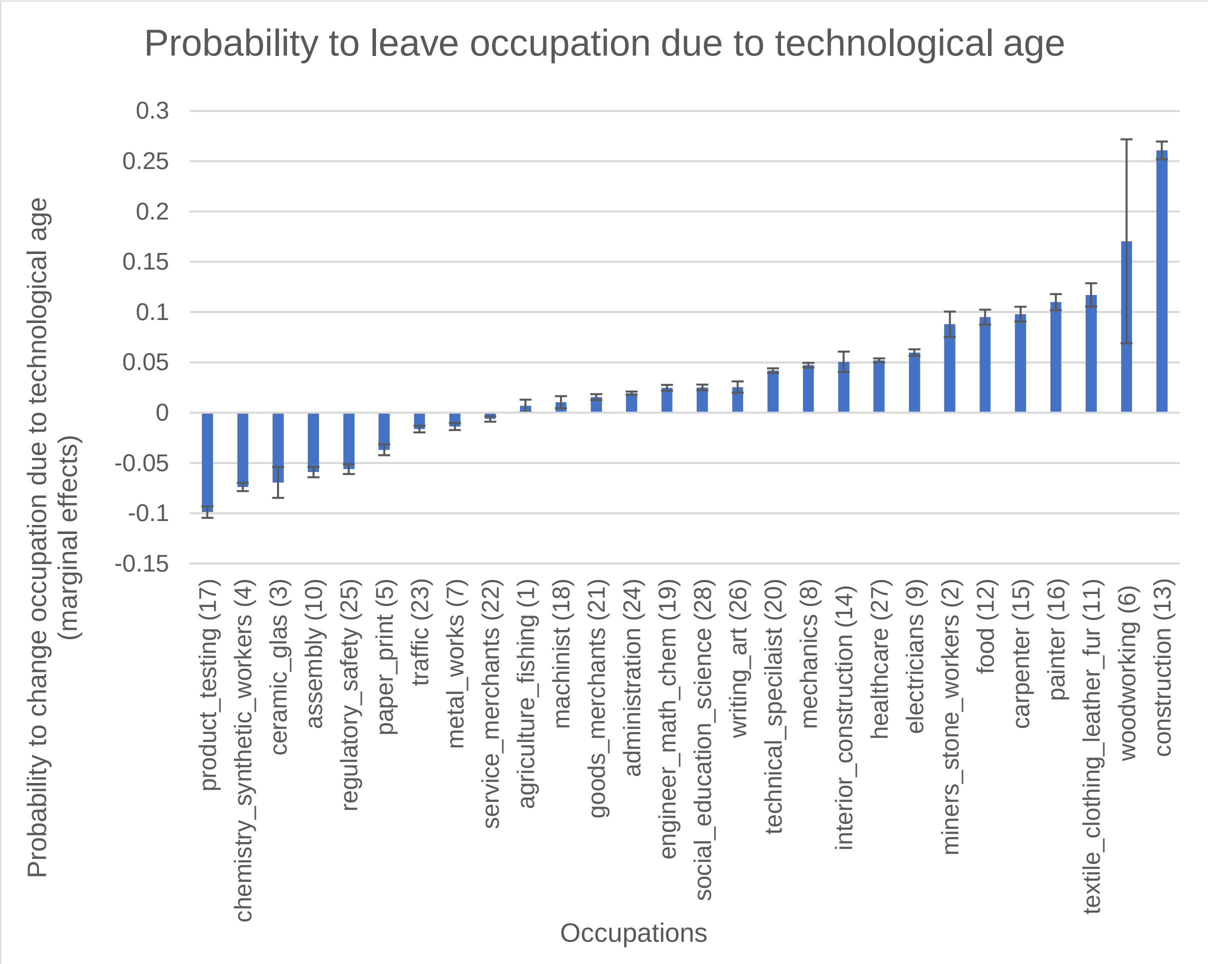

Figure 23: *Probability to leave occupation due to technological age*

Note: Marginal effects of regression (5) ordered by size. Including standard errors.

Figure 24 depicts the size of the marginal effect of the probability to leave an occupation due to technological age on the y-axis and the total technological that happened in each occupation between 1979 and 2006 on the x-axis. It is obvious to see that there is a negative correlation between the impact of technological age and total technological change. However, the graph is not only scattered, the marginal effects most to the right, i.e., the marginal effects with the most total technological change, are slightly positive again. Alas, due to the scattering of the data, it is very difficult to make a general assessment. The correlation between the likelihood to leave an occupation due to technological age and the total technological change per occupation is reported in *Table 16*, showing a correlation of -0.4918. *Figure 24* thus shows a generally negative linear distribution in which more technological change leads to a lower likelihood to leave the occupation, yet it could be possible that the correlation between the impact of technological age and total technological change is not linear. Alas, the graph does not provide clear information regarding this issue, mostly due to the marginal effects scattered to the far right in *Figure 24*, which are the occupations that have experienced the most technological change. In those occupations, the likelihood to leave due to technological age is very small but positive. This could suggest a parabolic trend in which the occupations with a medium amount of technological change are the ones staying in their occupations due to technological age, while in the occupations with the least technological change workers are being prompted to leave due to technological age and the occupations with the most technological change are experiencing almost not affected at all. A hint as to which of the two options is more likely, either the negative linear trend or the parabolic trend might be found when splitting the sample into smaller timeframes again. Of course, the same arguments as in Section *6.3* apply as 28 years constitute a long timeframe to analyze and the impact of technological age on the likelihood to leave occupations might have varied. Section *8.3* describes and analyzes the influence of technological age on the likelihood to leave ones' occupation in the same timeframe splits as Section *6.3*.

Naturally, this analysis has some weak points that must be pointed out. Firstly, while it is interesting to know whether workers are more likely to leave their occupation due to technological age, it is still unclear where the workers change to. It is not possible to say whether workers generally decrease their technological age when they change occupations. It would be especially interesting to know whether the employees that leave their occupations due to technological age decrease their technological age due to the occupation change. This leads to another problem, namely that the technological age is per definition tied to the occupation. This means that a person leaving a technologically intensive occupation, by definition must decrease his/her technological age while a person leaving a not technologically intensive occupation almost by definition must increase his/her technological age. This might make the interpretation of the likelihood to change occupations even more difficult. Thus far, especially workers employed in the less technologically intensive occupations have no mechanism to decrease their technological age.

Furthermore, unemployment is not part of this analysis, meaning that the workers leaving their occupation for unemployment are not included in the analysis. Therefore, in this analysis workers cannot become unemployed, either because they are laid off due to technological age, because they cannot keep up in their occupation, or because they want to decrease their technological age through an occupational change and are unable to do so due to the low technologically intensive nature of their occupation. This issue is addressed in Section *9.3* where unemployment is added into the data as a robustness check. Finally, workers leaving their occupation to go into early retirement are also not included in the sample. According to Ahituv and Zeira (2011), Bartel and Sicherman (1993) and Friedberg (2003), technological change can make older workers more likely to retire. The likelihood of workers leaving their occupations due to technological age might thus be underestimated.

Overall, technological age does seem to have an influence on workers leaving their occupation. Especially workers employed in occupations with less technological change are negatively affected by technological age and are more likely to leave their occupation due to technological age, in line with Hypothesis 3. Yet, apart from workers employed in less technologically intensive occupations, the impact of technological age on the probability to change occupations is a bit unclear. The most technologically intensive occupations seem do not be affected much by technological age while in the medium technologically intensive occupations technological age seems to make workers less likely to change occupation. The next section examines the probability to leave an occupation due to technological age in the three before used subsamples, *subsample 79, subsample 90* and *subsample 00*. Splitting the sample again helps to illuminate differences in the impact of technological age on the probability to leave an occupation across the timeframe.

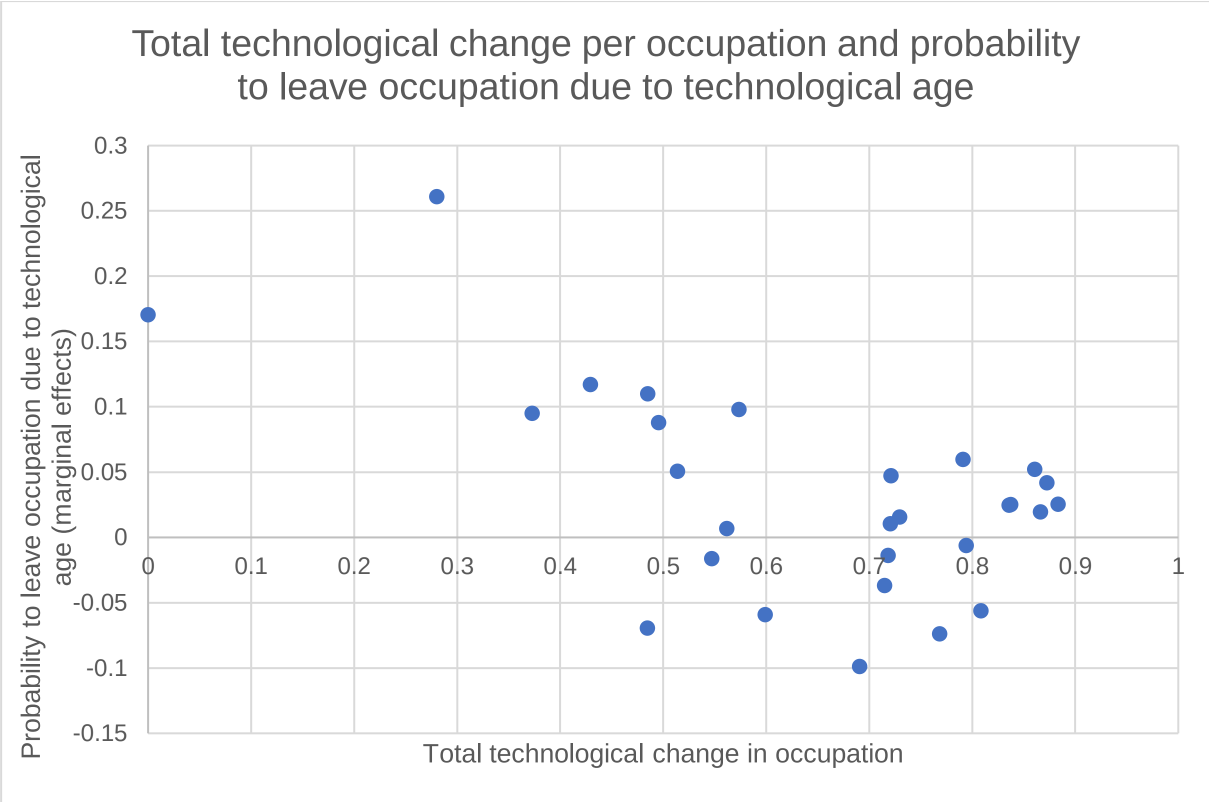

Figure 24: *Total technological change per occupation and probability to leave occupation due to technological age*

Note: Marginal effects of regression (5) and overall technological change per occupation from Table A3 to *Table A6.*

Table 17: *Linear correlation between the marginal effects of regression (5) and technological change per occupation*

Correlation between	Sample Period	Correlation
marginal effects likelihood to leave occupation	*overall sample*	-0.4918
technological change	*overall sample*	

Note: The correlation does not include the observation for woodworking (6).

8.3 Regression results *subsample 79, subsample 90* and *subsample 00*

This section takes regression (5) from Section *8.1* and re-estimates it again based on the three different time periods *subsample 79, subsample 90* and *subsample 00*. As in previous sections, the results from the three-time sub sample regressions are reported alongside the results of regression (5). Only the occupational marginal effects of technological age are reported, the full regression outputs can be found in Appendix *A14.iii.* The next section then examines the marginal effects in the established graphs, a bar graph with marginal effects of each time frame and the marginal effects of the *overall sample* ordered by size for reference. Finally, a plot of the marginal effects per occupation and the total technological change per occupation for the three subsamples and the *overall sample* is reported alongside a table showing the linear correlation between the likelihood to leave an occupation and the total technological change per occupation to quantify the correlation between the two.

Similarly to previous sections, the regressions reported in *Table 18* are described one by one. Regression (6), covering *subsample 79* utilizes 3,839,340 observations and achieves an R-squared of 0.0496. All marginal effects are significant at the 0.1 percent level. Interestingly, and contrary to regression (5), all marginal effects are positive and much larger. The smallest marginal effect is the one for service_merchants (22) at 0.0594[71] and the largest is food (12) with 2.9712. Considering this is more than ten times as large as the largest effect of technological age on the probability to change occupations in regression (5), the numbers from regression (6) seem large. Increasing technological age in the food (12) occupation by one percentage point during *subsample 79* would lead to a 2.9712 percent increase in the likelihood that a worker would leave the food (12) occupation. While these marginal effects seem too large to be real, it has to be kept in mind that the overall technological change in the food (12) occupation in *subsample 79* was from 0.0032 to 0.023, making 0.023 the highest possible technological age in the occupation. The coefficients thus have to be interpreted on the limited domain of the independent variable. While for a technological age of 0.5 the coefficient for food is much too large to be realistic, at a technological age of 0.023 the coefficient for food (12) can be realistic.

[71] While the largest marginal effect for regression (5) was construction (13) with 0.2608.

The regression for *subsample 90*, regression (7), has 4,371,323 observations and an R-squared of 0.0501. 5 out of the 28[72] coefficients are statistically significant at the one percent level. Again, all significant marginal effects are positive, meaning that an increase in technological age would lead to a higher probability of leaving one's occupation during *subsample 90*. The smallest significant marginal effect is the one for administration (24) with 0.0391 and the largest is the one for miners_stone_workers (2) with 1.0756. While these marginal effects are still much larger than the marginal effects of the *overall sample*, they are also significantly smaller than the marginal effects of *subsample 79*. Of course, the amount of possible technological age is already much higher in this timeframe (in fact reaching as far as 0.7689 for the administration (24) occupations). This changes the possible range of interpretation for the coefficients making smaller marginal effects seem reasonable.

The final regression, regression (8) for *subsample 00* has 2,819,888 observations and an R-squared of 0.0701. Coefficients for six occupations are insignificant[73]; the other 22 coefficients are significant at the five percent level. Furthermore, contrary to the last two regressions, most coefficients are negative and much smaller, comparable to the coefficients of regression (5). Just as in the regression for the *overall sample*, construction (13) has the largest significant marginal effect with 0.1359. Service_merchants (22) has the smallest marginal effect with -0.1770. For *subsample 00,* it can be said that there are more occupations where technological age would make a worker less likely to leave than there are occupations where technological age would make a worker more likely to leave.

Overall, technological age seems to have made workers more likely to leave an occupation in both *subsample 79* and *subsample 90* while in *subsample 00*, technological age has made workers rather less likely to leave their occupation. The size of the coefficients for the regression (6) and (7) is rather large; alas, the range of technological age where they can be interpreted can be limited. The next section covers the bar graphs with occupations ordered by the size of their marginal effects in the entire

[72] The occupations with the insignificant marginal effects are ceramic_glas (3), chemistry_synthetic_workers (4), product_testing (17), service_merchants (22) and regulatory_safety (25).
[73] The occupations with insignificant coefficients are miners_stone_workers (2), woodworking (6), electricians (9), textile_clothing_leather_fur (11), machinist (18) and writing_art (26).

sample period and finally the graph showing the relationship between the overall technological change in the timeframe and the size of the coefficients, and the correlation coefficients accompanied by a more in-depth interpretation of the results.

Table 18: *Regressions (5), (6), (7) and (8), the impact technological age on the likelihood to change occupations, overall sample, subsample 79, subsample 90 and subsample 00*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
agriculture_fishing (1)	.0068	2.1658***	0.5032***	-0.0610***
	(.0061)	(.1403)	(.0410)	(.0127)
miners_stone_workers (2)	0.0879***	1.0046***	1.0756***	.0167
	(.0126)	(.2947)	(.1842)	(.0225)
ceramic_glas (3)	-0.0694***	1.9840***	.1034	-0.0906*
	(.0153)	(.3556)	(.0543)	(.0440)
chemistry_synthetic_workers (4)	-0.0739***	0.2275***	-0.0173	-0.0658***
	(.0041)	(.0370)	(.0217)	(.0094)
paper_print (5)	-0.0369***	0.1342***	0.1322***	-0.0906***
	(.0054)	(.0336)	(.0364)	(.0137)
woodworking (6)	.1704	2.4964***	0.6451***	-0.1832
	(.1014)	(.3505)	(.1767)	(.1687)
metal_works (7)	-0.0138***	1.3648***	0.7878***	-0.0230***
	(.0035)	(.0680)	(.0679)	(.0063)
mechanics (8)	0.0472***	1.0657***	0.2961***	0.0211***
	(.0023)	(.0395)	(.0181)	(.0057)
electricians (9)	0.0598***	0.4146***	0.2733***	-0.0076
	(.0032)	(.0240)	(.0160)	(.0104)
assembly (10)	-0.0591***	1.0787***	0.3605***	-0.0478***
	(.0051)	(.0728)	(.0478)	(.0096)
textile_clothing_leather_fur (11)	0.1171***	2.9615***	0.7649***	.0266
	(.0116)	(.1737)	(.0969)	(.0211)
food (12)	0.0950***	2.9712***	0.8365***	0.0340*
	(.0074)	(.1483)	(.0517)	(.0156)
construction (13)	0.2608***	2.3684***	0.9925***	0.1359***
	(.0088)	(.1482)	(.0624)	(.0193)
interior_construction (14)	0.0506***	1.5288***	0.5551***	0.0400*
	(.0101)	(.1775)	(.0763)	(.0201)
carpenter (15)	0.0980***	1.7194***	0.4862***	0.0436**
	(.0073)	(.1184)	(.0482)	(.0168)
painter (16)	0.1099***	2.3965***	0.7380***	0.0760***
	(.0080)	(.1831)	(.0985)	(.0156)
product_testing (17)	-0.0989***	0.4844***	.0420	-0.1040***
	(.0057)	(.0425)	(.0378)	(.0129)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
machinist (18)	.0104	0.7535***	0.4457***	-0.0038
	(.0060)	(.0779)	(.0556)	(.0119)
engineer_math_chem (19)	0.0247***	0.1018***	0.0927***	-0.0970**
	(.0029)	(.0074)	(.0115)	(.0310)
technical_specilaist (20)	0.0418***	0.1856***	0.1185***	-0.0797***
	(.0023)	(.0086)	(.0084)	(.0178)
goods_merchants (21)	0.0155***	0.6156***	0.1563***	-0.0612***
	(.0029)	(.0188)	(.0124)	(.0102)
service_merchants (22)	-0.0063*	0.0594***	.0102	-0.1770***
	(.0027)	(.0064)	(.0131)	(.0237)
traffic (23)	-0.0163***	0.8995***	0.2328***	-0.0458***
	(.0033)	(.0455)	(.0249)	(.0082)
administration (24)	0.0194***	0.0942***	0.0391***	-0.1193***
	(.0016)	(.0051)	(.0068)	(.0167)
regulatory_safety (25)	-0.0561***	0.2376***	-0.0219	-0.1330***
	(.0049)	(.0283)	(.0144)	(.0203)
writing_art (26)	0.0255***	0.2545***	0.1455***	-0.0425
	(.0056)	(.0211)	(.0178)	(.0266)
healthcare (27)	0.0520***	0.3905***	0.0864***	-0.0443***
	(.0020)	(.0197)	(.0063)	(.0105)
social_education_science (28)	0.0251***	0.3550***	0.0955***	-0.0691***
	(.0028)	(.0252)	(.0100)	(.0107)
Constant	0.3665***	0.4599***	0.3840***	0.2606***
	(.0039)	(.0090)	(.0085)	(.0134)
N	11,030,551	3,839,340	4,371,323	2,819,888
R-sq	0.0515	0.0496	0.0501	0.0701

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

8.4 Regression discussion *subsample 79, subsample 90* and *subsample 00*

Similar to Section *6.4*, this section uses three of the of far established bar-graphs to report the effects of regression (6) - (8). As before, the marginal effects of regression (5), the regression over the *overall sample*, are reported alongside each of the subsample marginal effects. The marginal effects are ordered by increasing size of marginal effects in regression (5) along the x-axis while the size of the marginal effects is reported on the y-axis. The three graphs are then discussed individually. Finally, in this section *Figure 28* reports the marginal effects per occupation of regressions (6) - (8) in relation to the total technological change per occupation in the subsample accompanied by the correlation coefficients in *Table 19*.

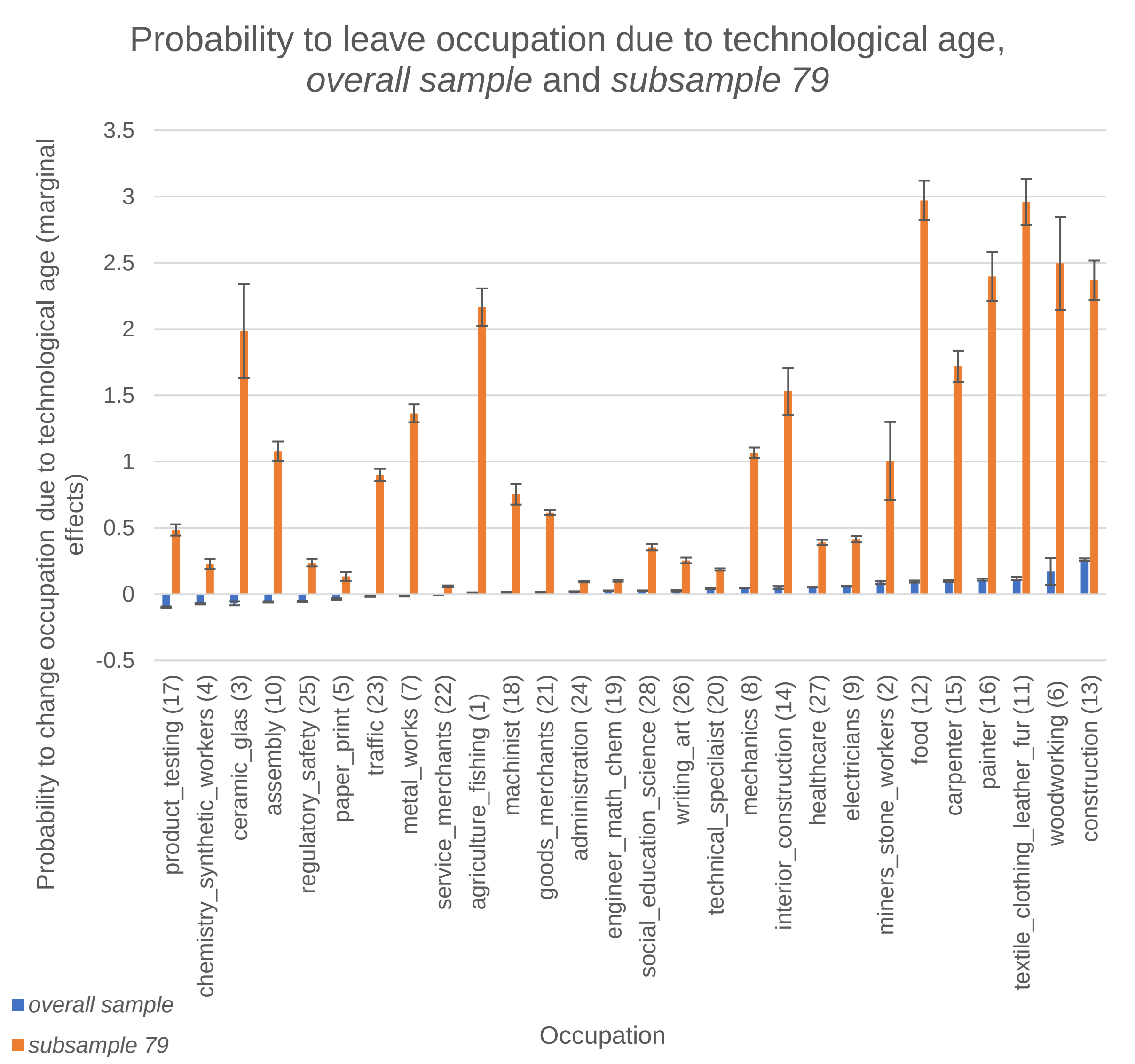

Figure 25: *Probability to leave occupation due to technological age, overall sample and subsample 79*

Note: Marginal effects of regression (5) and regression (6), ordered by size of marginal effects in regression (5) including standard errors.

Figure 25 shows the probability to leave an occupation due to technological age in *subsample 79* and the *overall sample*. The effects are ordered by increasing size of the marginal effects of the *overall sample,* regression (5) for easy comparison. As mentioned before, the results of the *subsample 79* regression are both, only positive and much larger than the *overall sample* results. However, the coefficients can only be correctly interpreted for a small amount of technological age. While there is not much of a trend visible when comparing the marginal effects of the two regressions, it can generally be said that the larger marginal effects of regression (6) are towards the right-hand side. This could indicate that either the positive *overall sample* marginal effects are (at least partly) driven by the marginal effects of *subsample 79*. In other words, the occupations where technological age makes workers more likely to leave in the *overall sample* period are generally also the same occupations where technological age makes workers more likely to leave their occupations in *subsample 79* timeframe. The *subsample 79* regression would capture the beginnings of the computerization era, showing the first impacts of technological age driven by the emergence of computers. While technological age cannot have been very high in most occupations, the effects of technological age on staying in or leaving an occupation are already visible.

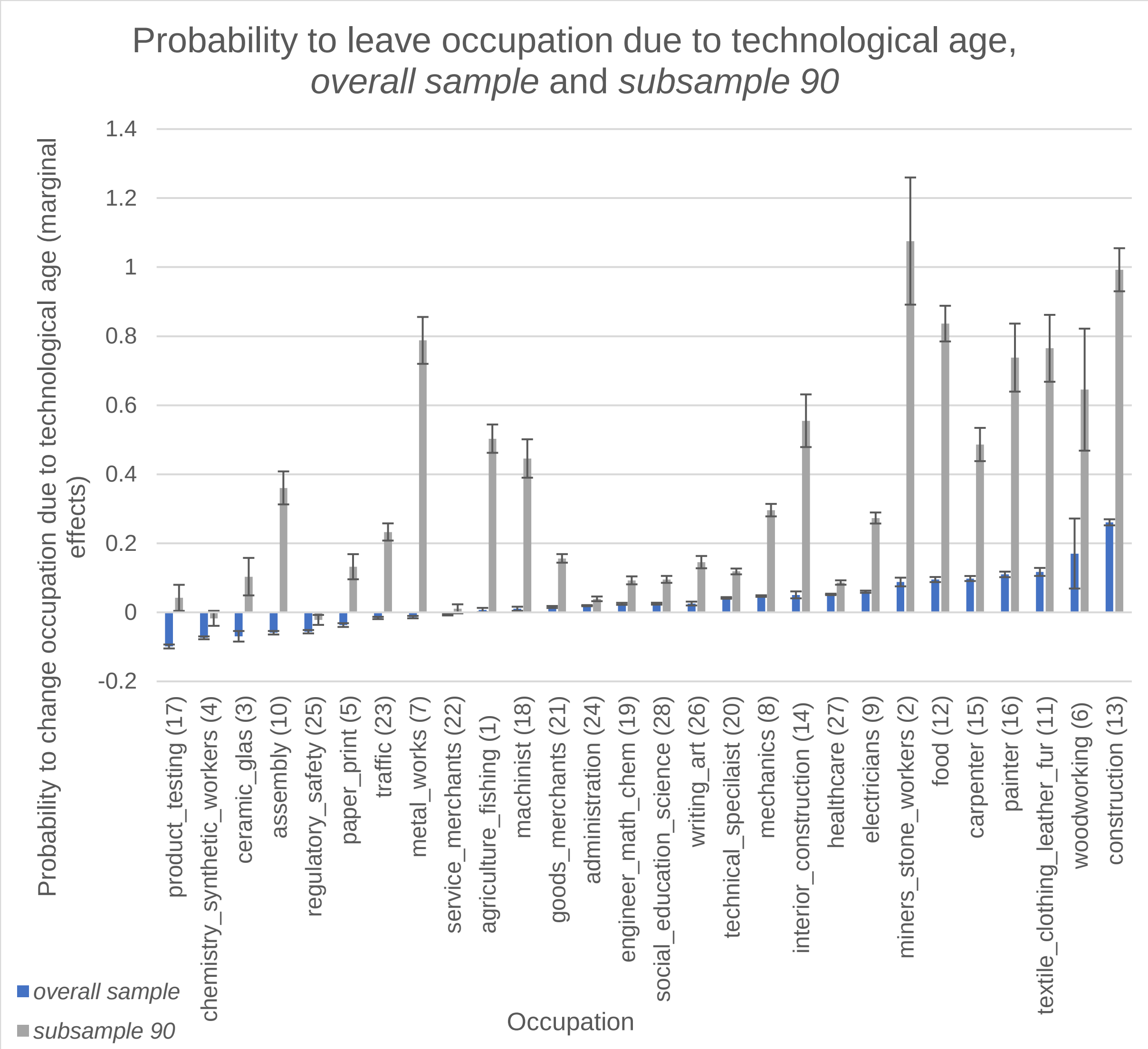

Figure 26: *Probability to leave occupation due to technological age, overall sample and subsample 90*

Note: Marginal effects of regression (5) and regression (7), ordered by size of marginal effects in regression (5) including standard errors.

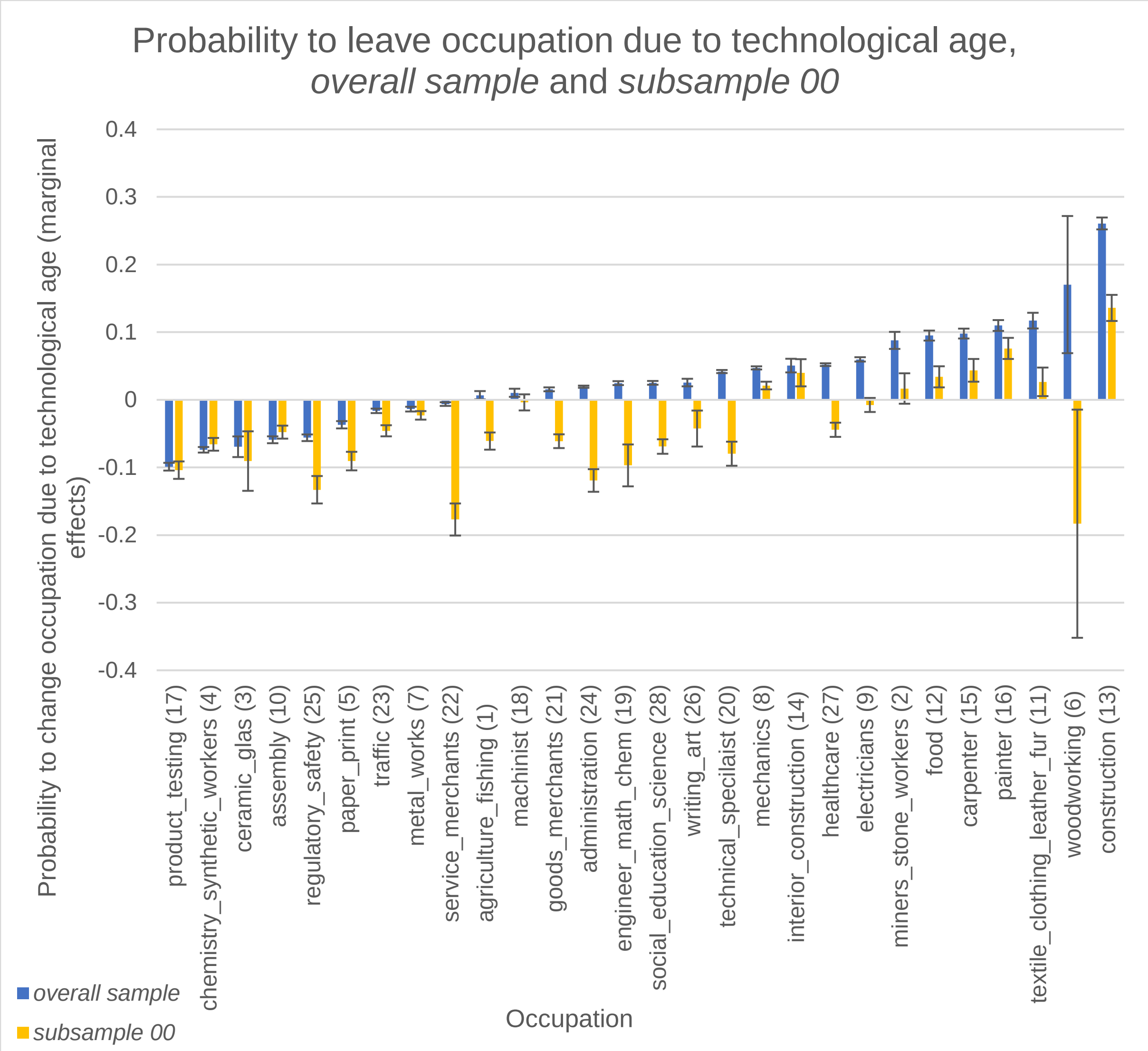

Figure 27: *Probability to leave occupation due to technological age, overall sample and subsample 00*

Note: Marginal effects of regression (5) and regression (8), ordered by size of marginal effects in regression (5) including standard errors.

Figure 26 depicts the probability to leave an occupation due to technological age in *subsample 90* and the *overall sample*. As in the last figure, all (significant) marginal effects are positive in *subsample 90* and much larger when compared to the *overall sample*. The reasoning behind the size of the marginal effects can be the same as for *subsample 79*. This would also make sense as the size of possible technological age has increased in *subsample 90* when compared to *subsample 79* and the size of the marginal effects has decreased in turn. Yet, the overall maximum of possible technological age is not reached yet which drives the marginal effects to be larger when comparing them to the marginal effects of the *overall sample* regression. As before, and even more pronounced, the large positive marginal effects of regression (7) are generally situated towards the right-hand side of the graph. The occupations in which technological age seems to make workers more likely to leave are thus similar in *subsample 79* and *subsample 90*. The positive marginal effects of the overall timeframe regression seem to be driven by both aforementioned time periods.

Figure 27 shows the probability to leave an occupation in *subsample 00* and the *overall sample*. Two things immediately come to mind, namely that in *subsample 00* most marginal effects are not positive and that the size of the marginal effects is much more in line with the size of the marginal effects of the *overall sample* regression. Interestingly, the (significant) positive marginal effects are once again on the right-hand side of the graph, continuing the trend from *Figure 25* and *Figure 26*. However, the number of significant positive coefficients is very small in the *subsample 00* regression so that overall, it can be said that in this time period workers are not more likely to change occupations due to technological age but rather are even generally more likely to stay in their occupations.

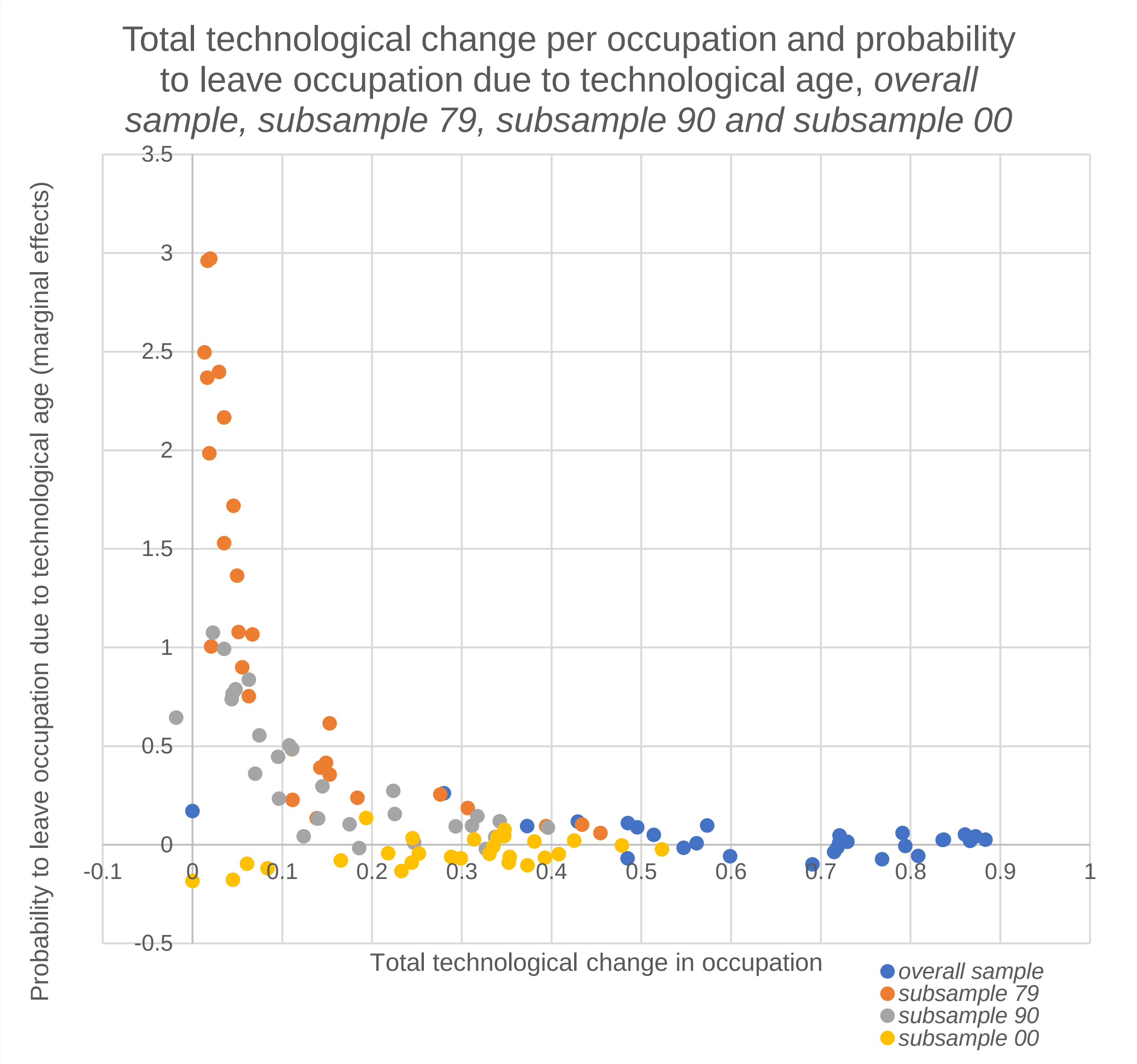

Figure 28: *Total technological change per occupation and probability to leave occupation due to technological age, overall sample, subsample 79, subsample 90 and subsample 00*

Note: Marginal effects of regressions (5)-(8) and overall technological change per occupation according to Table A3 to *Table A6 in each timeframe.*

Table 19: *Linear correlation between the marginal effects of regressions (5)-(8) and technological change per occupation in each timeframe*

Correlation between	**Sample Period**	**Correlation**
marginal effects likelihood to leave occupation technological change	*overall sample* *overall sample*	-0.4918
marginal effects likelihood to leave occupation technological change	*subsample 79* *subsample 79*	-0.7047
marginal effects likelihood to leave occupation technological change	*subsample 90* *subsample 90*	-0.7838
marginal effects likelihood to leave occupation technological change	*subsample 00* *subsample 00*	0.3904

Note: The correlation does not include the observation for woodworking (6).

Figure 28 shows the correlation between the marginal effects of regressions (6) - (8) and the overall technological change per occupation. The first thing coming to mind is that in *subsample 79* and *subsample 90*, there is a clear negative trend between the total technological change per occupation and the likelihood to leave an occupation due to technological age. This negative correlation in *subsample 79* and *subsample 90* is further supported by the correlation numbers in *Table 19*, showing a correlation of -0.7047 and -0.7838 respectively. These correlations are much stronger than the negative correlation of -0.4918 for the *overall sample*. Interestingly, the impact of technological age on the likelihood to leave an occupation has a positive correlation with the total technological change per occupation in *subsample 00*. Here the correlation is 0.3904. This means that in *subsample 00*, workers employed in occupations with more technological change are more likely to leave their occupation due to technological age. This phenomenon could come back to a discussion in Section *6.4*, namely that the occupations with a large amount of technological age during the *overall sample* had reached very high levels of technology already in 2000. This makes the occupations with a large amount of technological change in *subsample 00* not the same occupations that experienced a large amount of technological age across the entire sample period. This problem is further discussed in Section *10 Combining wage analysis and occupation change analysis results.*

Generally, it can be said that while technological age has an impact on workers' decision to leave occupations, that impact is not constant over time. Especially in the years 1979-1999, technological age seems to make workers form particularly low technology intensive occupations more likely to leave their occupation. This further supports Hypothesis 3, stating that technological age should make workers more likely to leave occupations. However, again this trend is hurting the less technology intensive occupations more. The trend of technological age hurting the less technology intensive occupations more is then reversed for *subsample 00*, where technological age generally seems to make people less likely to leave their occupation. Overall, these trends are quite opposite to the trends of the wage analysis, where in *subsample 79* and *subsample 90* log technological age seemed to have a positive impact on log wages and in *subsample 00* log technological age had an overwhelmingly negative effect on log wage. This connection is further explored in Section *10*.

The next section depicts the results of regression (5) using *KldB2010* instead of *KldB88* in order to check for robustness in the same way that using the *KldB2010* was used to check for robustness in the wage sections. As this is simply a robustness check, only the bar graphs of the marginal effects and the correlation between the likelihood to leave and occupation and the total technological change per occupation is reported, the detailed regression outputs can be found in Appendix *A15.i*.

9 Robustness checks occupation change analysis

9.1 Regression *overall sample* using *KldB2010*

Similar to the wage analysis, the job change analysis also repeats the *overall sample* regression and the sub sample regressions using the *KldB2010*[74] occupation classification instead of the *KldB88* occupation classification. As mentioned before, a large part of the analysis hinges on the correct assortment of occupation classifications and the corresponding technological change numbers. Using a different classification for the regression should help to check for robustness of the foundational concepts of the analysis. In this section, the analysis of Section *8.1* is repeated using *KldB2010* instead of *KldB88*. As before, the detailed regression outputs can be found in Appendix *A15.i*, here, only *Figure 29*, the bar graph ordering the marginal effects by size along the x-axis and *Figure 30*, the graph showing the relationship between technological change per occupation and probability to leave an occupation are depicted. Furthermore, *Table 20* reports the linear correlation between the likelihood to leave an occupation and the total technological change per occupation.

Figure 29 shows the probability to leave one's occupation due to technological age when using *KldB2010* for the *overall sample* regression. The marginal effects of the occupations are ordered by size, the smallest on the left-hand side and the largest on the right. There are 10 occupations with negative marginal effects, 7 occupations with insignificant marginal effects[75] and 21 occupations with a positive marginal effect. The distribution in *Figure 29* is similar to the distribution in *Figure 23* (the same regression with *KldB88* occupation classification) in many ways. The marginal effects in *Figure 29* are similar in size when compared to the ones in *Figure 23*, the kind of occupations on the right-hand side are similar in their overall technological change experienced. The occupations with the largest probability of workers leaving due to technological age in *Figure 29* are construction (32) with a marginal effect of 0.2417, interior

[74] The explanatory statistics for the *KldB2010* occupation change analysis can be found in Appendix *A10*
[75] Gardening (12), plastic_wood_process (22), metal_making (24), purchasing_sales (61), finance (72), education (83) and marketing (92) have insignificant marginal effects.

construction (33) with 0.1277, cleaning_service (54) with 0.1103 and textile_processing (28) with 0.1041. In *Figure 23*, the occupation with the largest (significant) marginal effects were construction (13) with a marginal effect of 0.2608, textile_clothing_leather_fur (11) with 0.1171, painter (16) with 0.1099 and carpenter (15) with 0.098. All these occupations are not technologically intensive by nature. The trend that the occupations with less technological change being affected more negatively by technological age than occupations with more technological change continues regardless of the occupation classification.

The occupations in which workers are least likely to leave due to technological age in *Figure 29* are logistics (51), IT (43), safety (53), law (73) and social science (91). These five occupations are very technologically intensive which contrasts with the occupations where workers are least likely to leave when using the *KldB88*. Here, the occupations are ceramic_glas (3), chemistry_synthetic_workers (4), paper_print (5), assembly (10), product_testing (17) and regulatory_safety (25) which, as mentioned in Section *5.1.4,* are rather middle of the pack when it comes to total technological change across the sample period. However, while when using the *KldB88* the five occupations with the most technological change had negative marginal effects, the overall trend when depicting the relationship between total technological change and probability to leave occupation was still strongly negative. In fact, using the *KldB2010* only shows an even less spread-out negative relationship between marginal effects and total technological change, as depicted in *Figure 30*. Overall, the relationship between probability to leave an occupation due to technological age and total technological change is very similar between the regressions using either *KldB88* or *KldB2010* as *Figure 24* and *Figure 30* show.

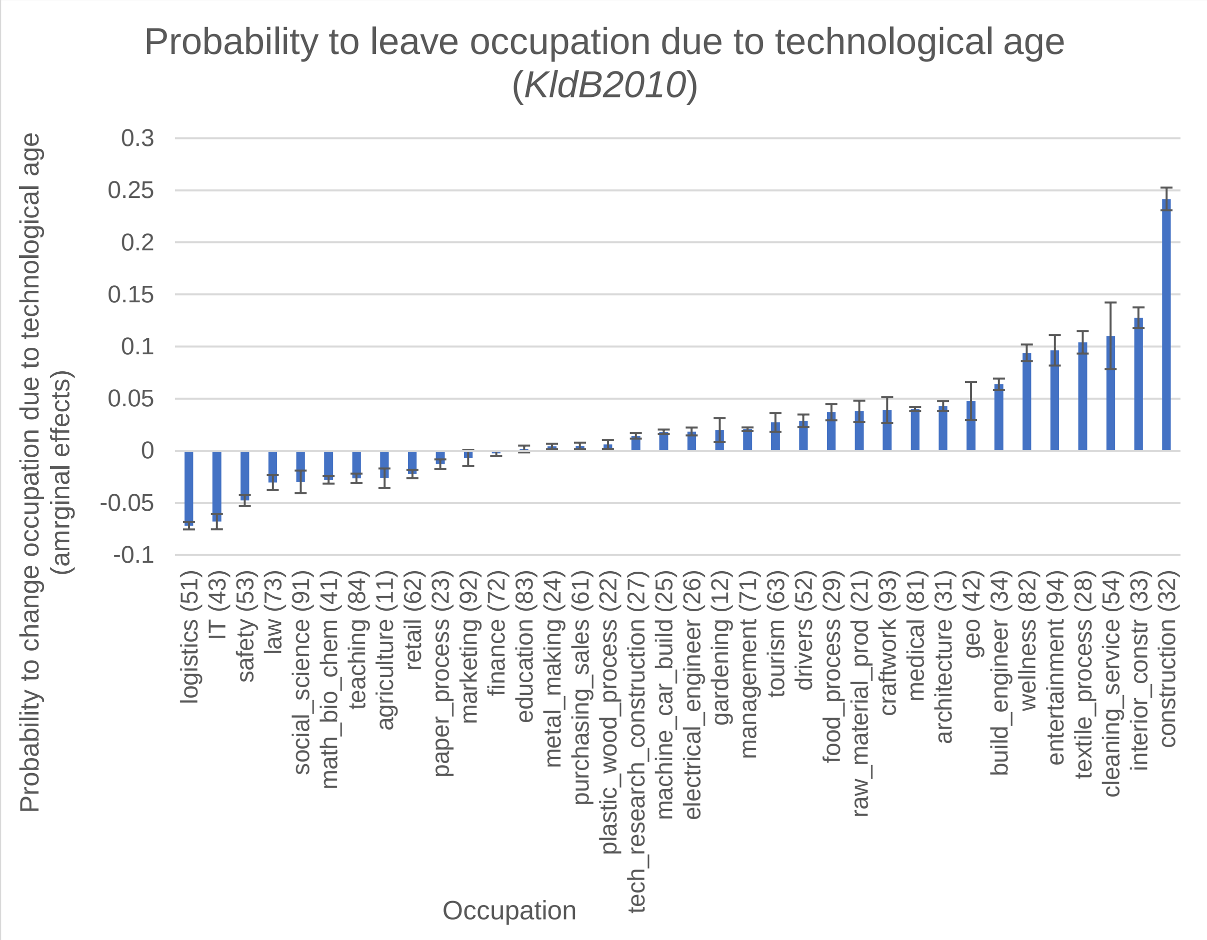

Figure 29: *Probability to leave occupation due to technological age (KldB2010)*

Note: Marginal effects of regression (18) ordered by size. Including standard errors. Regression (18) can be found in Table A62.

Figure 24 and *Figure 30* both show a negative relationship between the probability to leave an occupation and the total technological change experienced in an occupation. This assessment is supported by the linear correlation given in *Table 17* and *Table 20*. The correlation between the likelihood to leave an occupation using the marginal effects of the *KldB88* regression [regression (5)] is -0.4918. Using the *KldB2010* yields a correlation of -0.6114 for the probability to leave an occupation due to technological age with total technological change per occupation. The trend that less technologically intensive occupations are hurt more by technological age when compared to more technologically intensive occupations does not only continue when it comes to workers leaving their occupations, it also seems to be robust to changing the occupation classification. Overall, the results when using the *KldB88* and the *KldB2010* are very similar in size and in the kind of occupation with positive and negative marginal effects.

In order to test whether the findings of the time sub samples are also robust to changing occupation classifications, the next section again uses the split time samples, *subsample 79, subsample 90* and *subsample 00,* to test whether changing occupation classifications does affect the results from Section *8.3*. Similar to this section, the detailed regression outputs are only reported in Appendix *A15.ii*, Section *9.2* only depicts the marginal effects of the regressions using the established graphs.

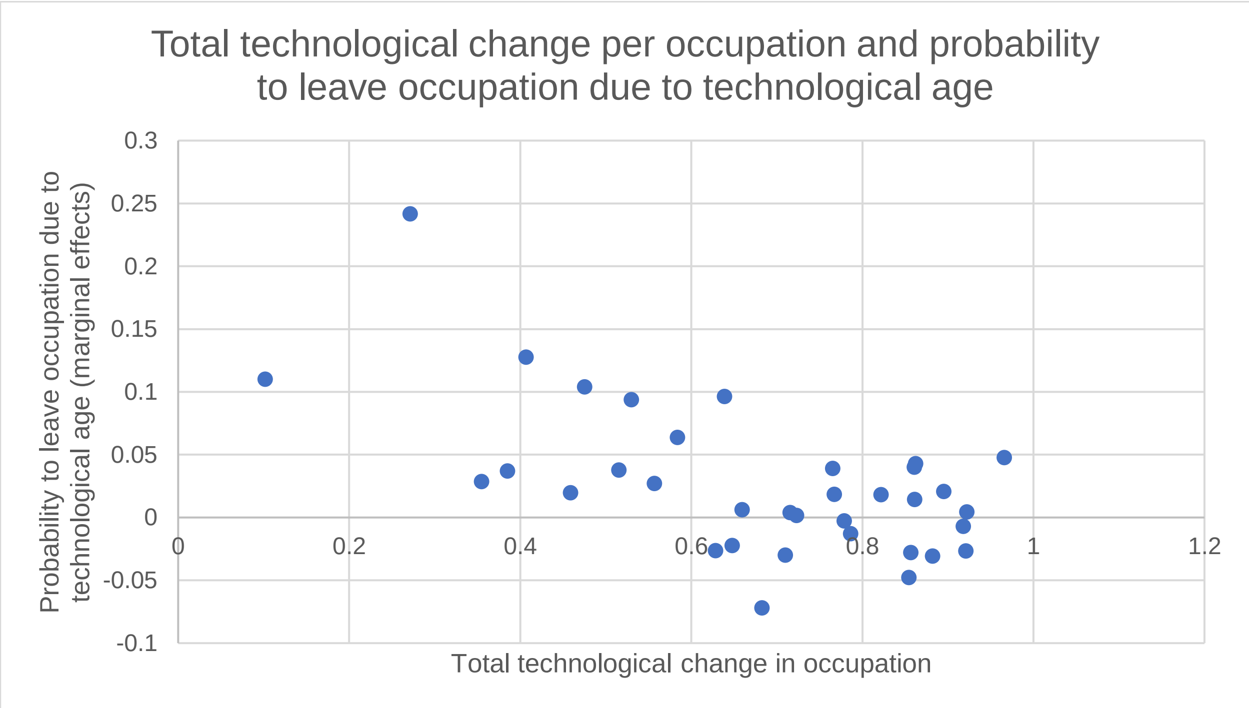

Figure 30: *Total technological change per occupation and probability to leave occupation due to technological age*

Note: Marginal effects of regression (18) and overall technological change per occupation from Table A11 to Table A15. Regression (18) can be found in Table A62.

Table 20: *Linear correlation between the marginal effects of regression (18) and technological change per occupation*

Correlation between	**Sample Period**	**Correlation**
marginal effects likelihood to leave occupation *(KldB2010)*	*overall sample*	-0.6114
technological change *(KldB2010)*	*overall sample*	

Note: The correlation does not include the observation for IT (43).

9.2 Regressions *subsample 79, subsample 90* and *subsample 00* using *KldB2010*

This section estimates regressions (6) - (8) again for the three subsamples, *subsample 79, subsample 90* and *subsample 00,* using *KldB2010* instead of *KldB88*. As before, only the bar graphs for each time period ordering the coefficients by size alongside regression (18), the *KldB2010 overall sample* regression, and the graph reporting total technological change per occupation and the size of the marginal effects per occupation are reported here[76]. Following the structure of the sections before, the bar graph for each subsample, *Figure 31* to *Figure 33* is discussed separately, pointing out similarities and differences to *Figure 25* - *Figure 27*. This section then concludes with the analysis of *Figure 34* depicting the total technological change per occupation in the subsample and the probability to leave an occupation due to technological age accompanied by *Table 21* depicting the linear correlation of the likelihood to leave an occupation due to technological age and total technological change per occupation..

[76] Detailed regression outputs can be found in Appendix *A15.ii.*

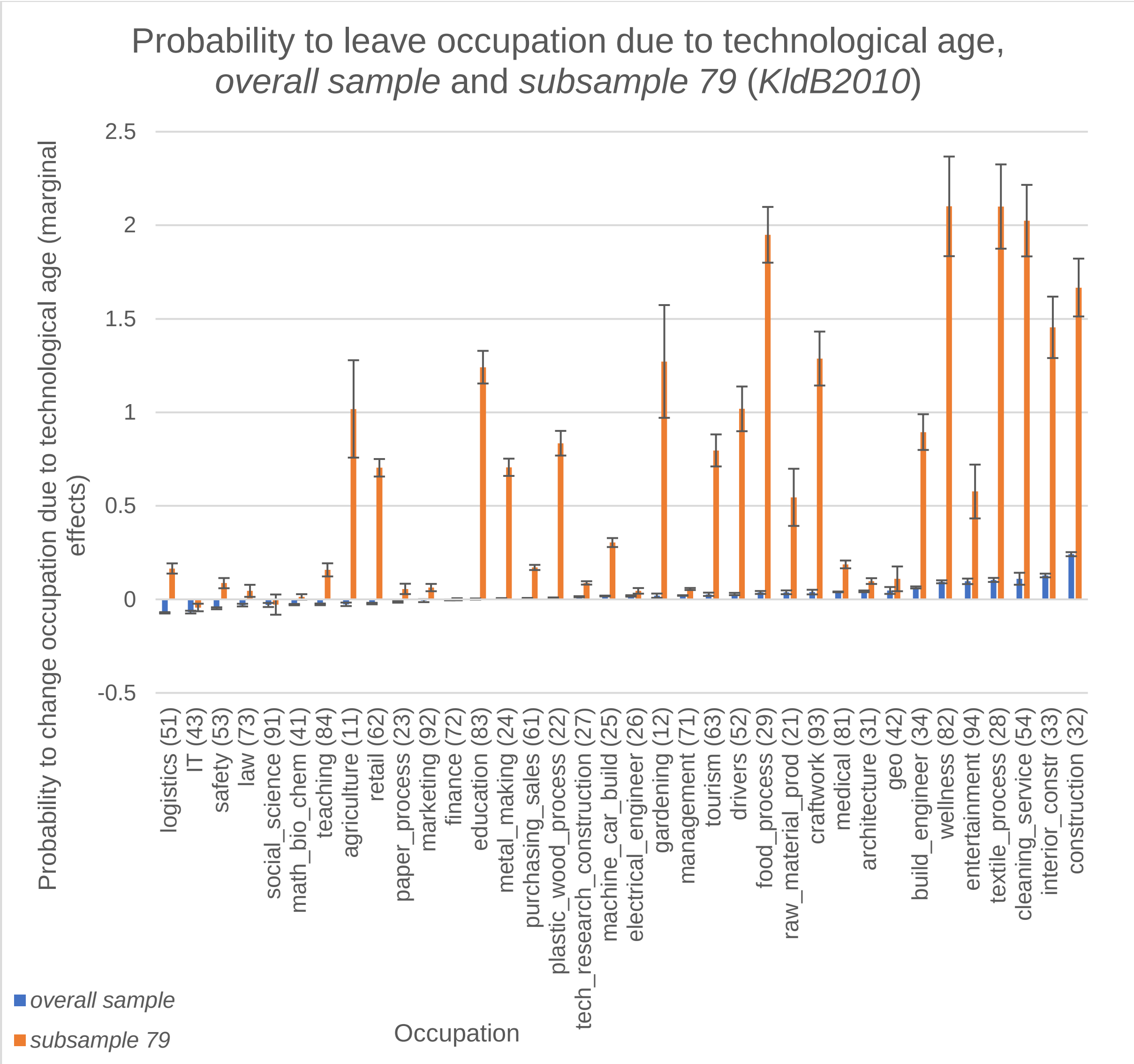

Figure 31: *Probability to leave occupation due to technological age, overall sample and subsample 79 (KldB2010)*

Note: Marginal effects of regression (18) and regression (19), ordered by size of marginal effects in regression (18) including standard errors. Regression (18) and (19) can be found in Table A63.

Figure 31 depicts the probability to leave an occupation due to technological age using *KldB2010* both, in *subsample 79* and in the *overall sample*. As before, the effects are ordered by increasing size of the marginal effects of the *overall sample* regression. The first thing coming to mind when looking at the marginal effects of the *subsample 79* marginal effects in *Figure 31* is that all significant marginal effects are positive. Furthermore, the size of the marginal effects is much larger for the *subsample*

79 regression when compared to the *overall sample* regression. In fact, the size of the marginal effects in *Figure 31* is a bit smaller than the size of the marginal effects of the *subsample 79* regression using *KldB88*. The large positive marginal effects are the same in *Figure 31* as they were for regression (6) in *Figure 25*. Not only does this mean that technological age makes workers more likely to leave their occupation in *subsample 79*, the effects do not differ much when comparing regressions utilizing *KldB88* or *KldB2010*. Furthermore, the larger positive marginal effects of the *subsample 79* regression are once again towards the right-hand side of *Figure 31,* even more so than in *Figure 25*, giving another reason to believe that the regression results are robust when it comes to changing occupation classifications. The reasoning behind the size of the marginal effects was discussed in Section *8.3* and *8.4*.

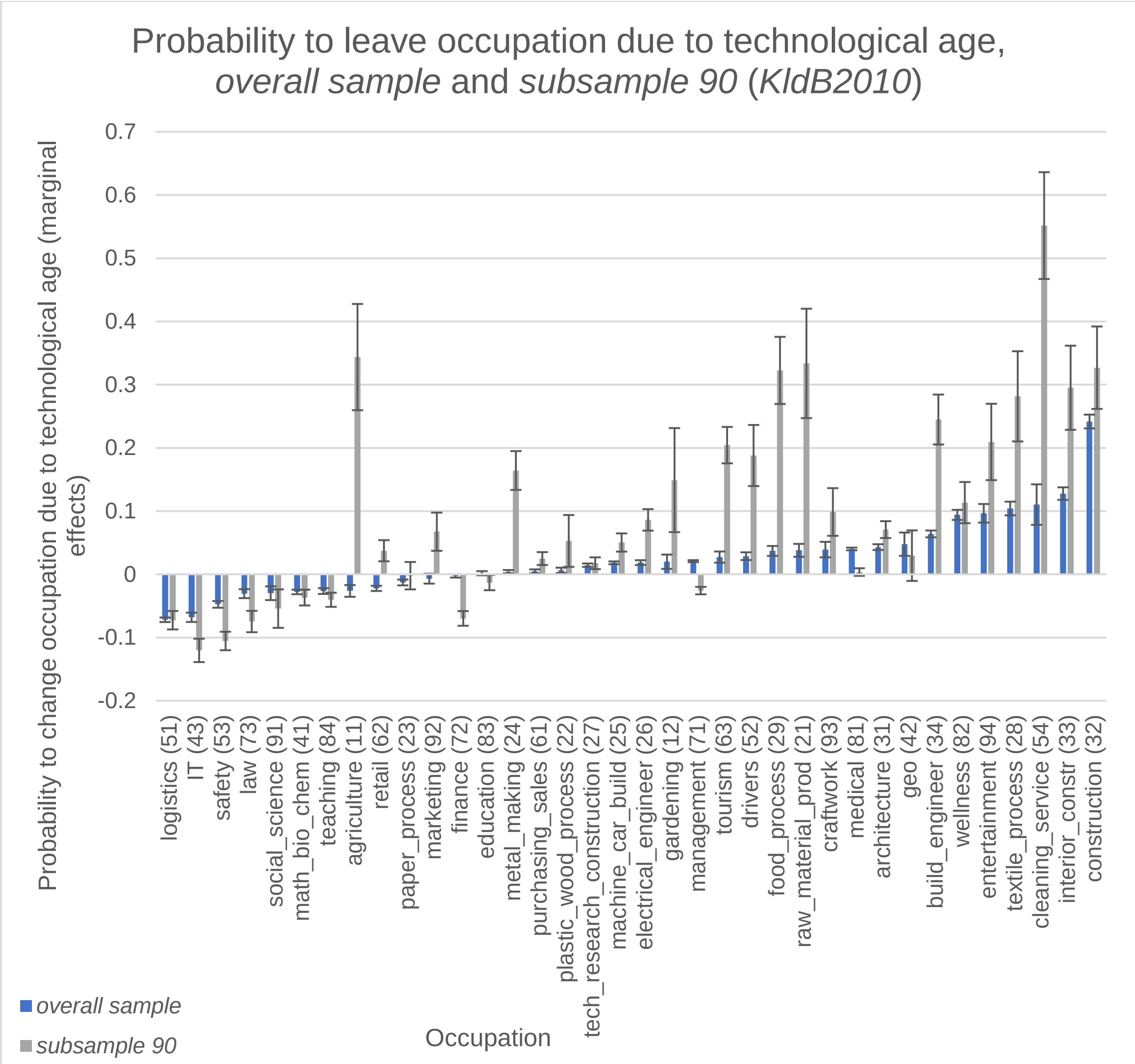

Figure 32: *Probability to leave occupation due to technological age, overall sample and subsample 90 (KldB2010)*

Note: Marginal effects of regression (18) and regression (20), ordered by size of marginal effects in regression (18) including standard errors. Regression (18) and (20) can be found in Table A63.

Figure 32 shows the probability to leave an occupation due to technological age in *subsample 90* and the *overall sample* using the *KldB2010* classification. Again, most marginal effects of the *subsample 90* regression are positive, the size of the negative marginal effects is similar to the negative marginal effects of the *overall sample* regression. The size of the positive marginal effects of the *subsample 90* regression are also larger than the marginal effects of the *overall sample* regression. Both, the size of the observations and the presence of the negative observations are slightly different from the observations in *Figure 26,* depicting the marginal effects for the same two regressions using *KldB88*. However, the general trend of larger positive observations situated towards the right-hand side of the graph is similar, as well as the size of the effects. Overall, *Figure 32* shows that the marginal effects from regression (7) are also rather robust to changing occupation classifications.

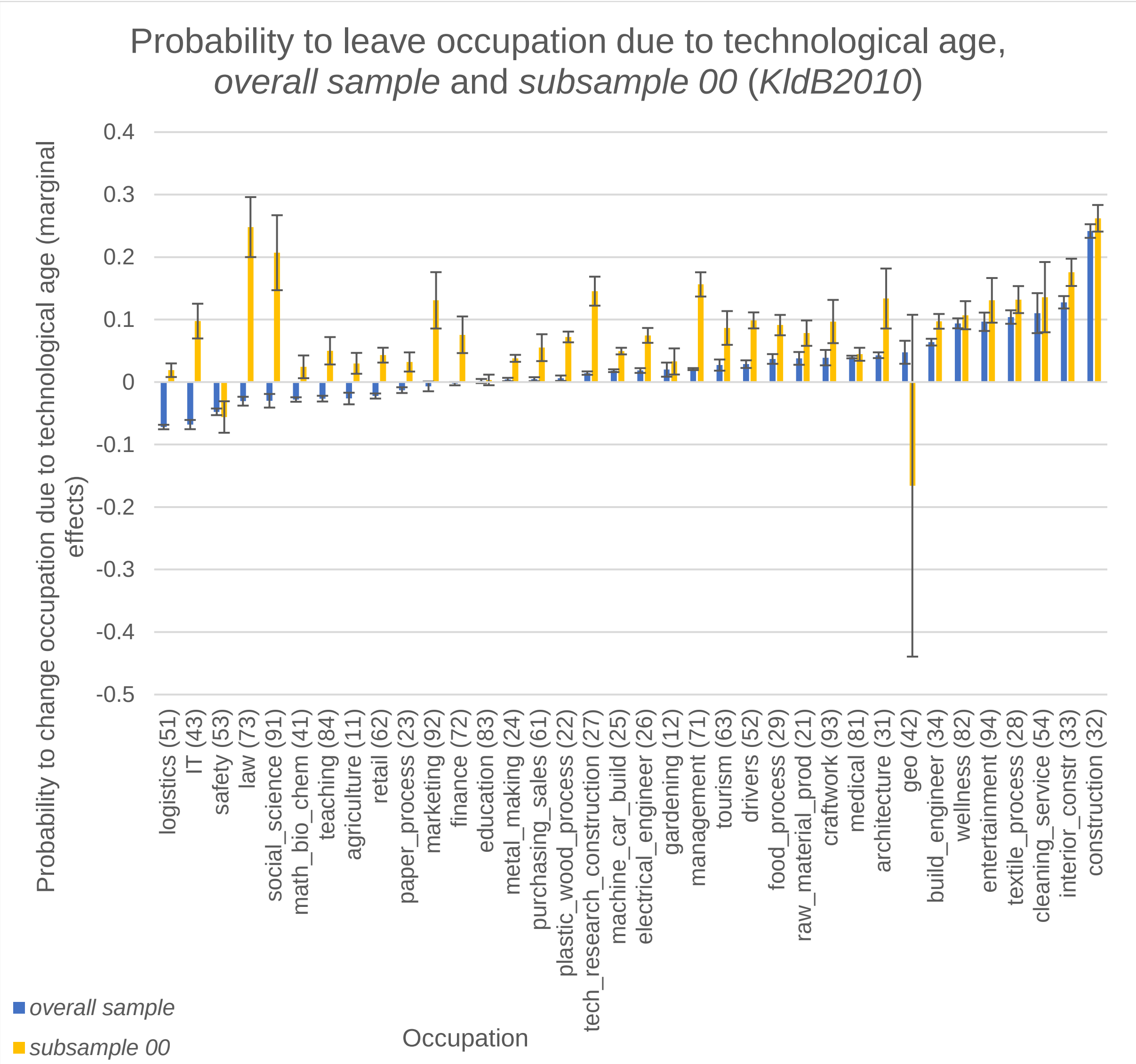

Figure 33: *Probability to leave occupation due to technological age, overall sample and subsample 00 (KldB2010)*

Note: Marginal effects of regression (18) and regression (21), ordered by size of marginal effects in regression (18) including standard errors. Regression (18) and (21) can be found in Table A63.

Figure 33 shows the probability to leave an occupation due to technological age in *subsample 00* and the *overall sample*. Alas, the marginal effects depicted in *Figure 33* differ substantially from the results shown in *Figure 27*. Where the *subsample 00* regression using *KldB88* resulted in only very few positive marginal effects, the regression using *KldB2010* yields almost exclusively positive marginal effects. Furthermore, the marginal effects of the *KldB2010* regression in *subsample 00* on the right-hand side of the graph are very close in size to the marginal effects of the of the *overall sample KldB2010* regression. Strikingly, the marginal effects of the *subsample 00 KldB2010* regression are the first set of robustness checks that are very dissimilar when compared to their *KldB88* counterpart. Contrary to the *KldB88* results from *subsample 00*, the results from the *KldB2010* regression of *subsample 00* suggest that during this timeframe workers in almost all occupations were more likely to change out of their occupation due to technological age. The finding that technological age makes workers generally more likely to stay in their respective occupation in *subsample 00* cannot be supported with the results in *Figure 33*. Unlike the results from *subsample 79* and *subsample 90*, the results from *subsample 00* seem not to be as robust to changing occupation classifications. Yet, considering the results of regression (8) are very much contrary to Hypothesis 3, that technological age should make workers more likely to leave their occupations, it should be noted that the results least supporting Hypothesis 3 are not as robust while the results from *subsample 79* and *subsample 90*, which are much more in line with Hypothesis 3, seem robust to changing occupation classifications.

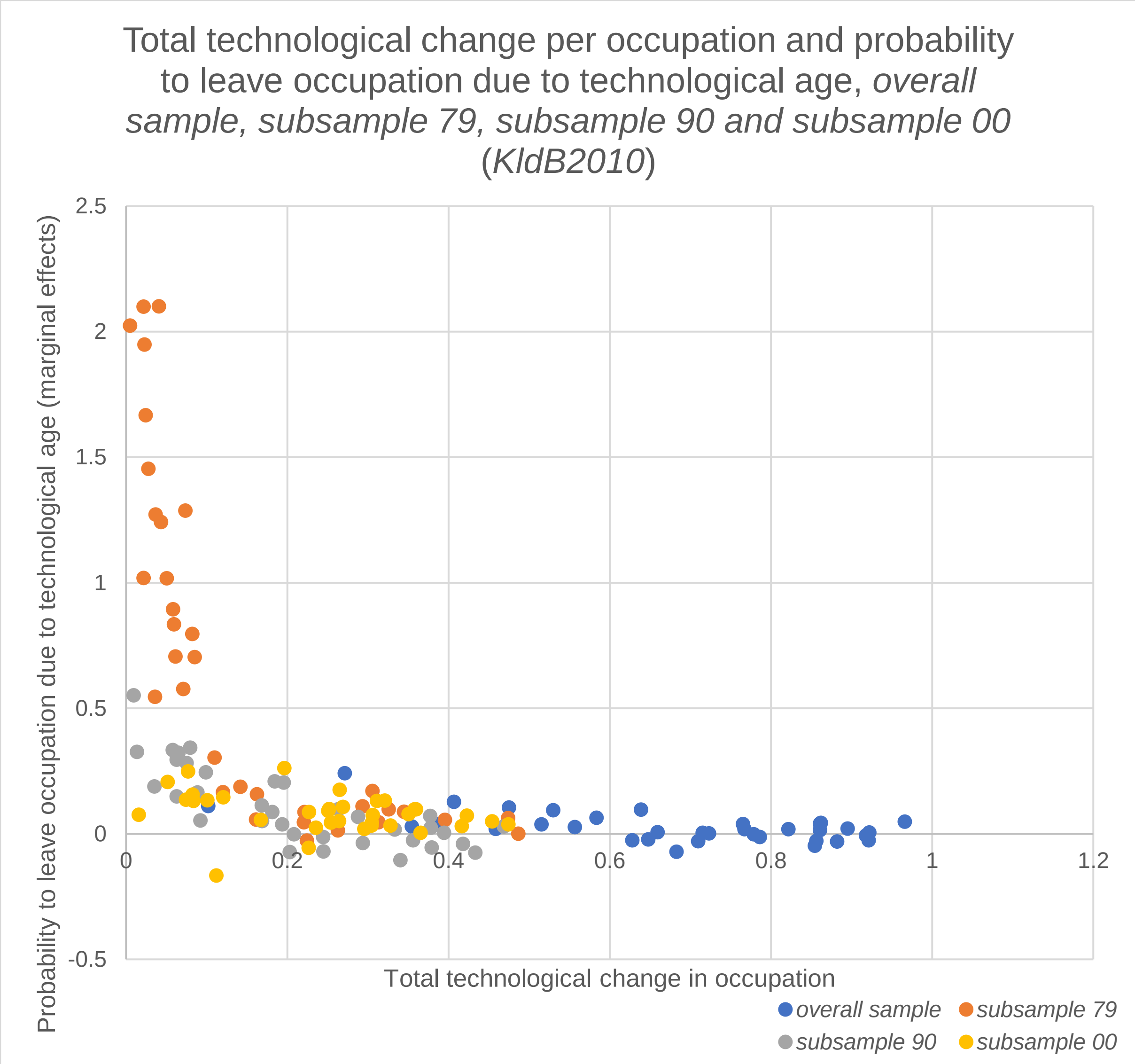

Figure 34: *Total technological change per occupation and probability to leave occupation due to technological age, overall sample, subsample 79, subsample 90 and subsample 00 (KldB2010)*

Note: Marginal effects of regressions (18)-(21) and overall technological change per occupation according to Table A11 to Table A15 in each timeframe. Regression (18) to (21) can be found in Table A63.

Table 21: *Linear correlation between the marginal effects of regressions (18)-(21) and technological change per occupation*

Correlation between	**Sample Period**	**Correlation**
marginal effects likelihood to leave occupation *(KldB2010)*	*overall sample*	-0.6114
technological change *(KldB2010)*	*overall sample*	
marginal effects likelihood to leave occupation *(KldB2010)*	*subsample 79*	-0.7474
technological change *(KldB2010)*	*subsample 79*	
marginal effects likelihood to leave occupation *(KldB2010)*	*subsample 90*	-0.7771
technological change *(KldB2010)*	*subsample 90*	
marginal effects likelihood to leave occupation *(KldB2010)*	*subsample 00*	-0.3155
technological change *(KldB2010)*	*subsample 00*	

Note: The correlation does not include the observation for IT (43).

Figure 34 shows the correlation between the influence of technological age to leave occupations and the overall technological change per occupation using *KldB2010*. Similar to *Figure 28*, showing the same relationship for the *KldB88* regression, the *subsample 79* and *subsample 90* results show a clear negative trend between the total technological change per occupation and the likelihood to leave an occupation due to technological age. The striking similarity is further shown by the quantified linear correlations. In *subsample 79,* the correlation between the likelihood to leave an occupation due to technological age and the total technological age experienced per occupation is -0.7474 when using *KldB2010* and -0.7047 when using *KldB88* as *Table 19* and *Table 21* show. The same goes for *subsample 90* where the correlation using *KldB2010* was -0.7771 and -0.7838 when using *KldB88*. Not only are these correlations almost the same but they also point towards the robustness of the trend that while workers in all occupations are more likely to leave their occupation due to technological age in *subsample 79* and *subsample 90,* the less technologically intensive occupations are affected more strongly.

Starkly different is the correlation between the influence of technological age on the likelihood to leave an occupation and the total technological change per occupation in *subsample 00*. Not only does *Figure 34* show a negative trend, *Table 21* shows a linear correlation of -0.3155. This is a complete contrast to the correlation shown in *Figure 28* and *Table 19.* When using *KldB88*, the correlation between the influence of technological age on the likelihood to leave an occupation and the total technological change per occupation in *subsample 00* was 0.3904. As mentioned before, regression (8) for *subsample 00* does not seem to be robust to changing occupation classifications, the positive correlation of the *KldB88* regression is not confirmed by the *KldB2010* regression.

All in all, the results of regression (6) and (7) show similar results even when changing the occupation classification to *KldB2010* and thus seem to be robust to occupation classification changes. Not only are the marginal effects similarly positive, the size of the marginal effects is also of similar scope. The results for regression (8) are in contrast not robust to occupational classification change. The marginal effects are wildly different when using *KldB2010*, the results from regression (21) supporting Hypothesis 3 when the results from regression (8) do not. The effect that technological age makes workers more likely to leave their occupation during *subsample 79* and *subsample 90* is thus robust to occupational classification change, while the finding that this effect reverts for *subsample 00* is not robust.

While the results so far have been overall rather robust, this analysis has ignored the change from an occupation to unemployment and has only looked at a change from one occupation to another. Of course, this could potentially lead to the omission of one of the most prevalent causes of changing occupation. That is why the next section introduces unemployment into the analysis and explores whether the findings change when workers can become unemployed as well as change to another occupation.

9.3 Regressions *overall sample* allowing for unemployment

While the effects of technological age on the likelihood to leave an occupation have been shown and tested for robustness concerning changing occupations, the analysis has ignored changes from an occupation to unemployment so far. This section reestimates regression (5) again but this time includes changes into unemployment as well. This way, workers cannot only leave their occupation for another occupation, they can also leave their occupation to become unemployed. As in all robustness sections, only the bar graph with the size of the occupation specific marginal effects of technological age is reported here, in this case with the marginal effects from regression (5) and *Figure 23: Probability to leave occupation due to technological age* for reference. The full regression outputs can be found in Appendix *A15.iii*. This section also reports the correlation between the marginal effects from the regression with unemployment and total technological change per occupation as well as the correlation between the marginal effects of regression (5) without unemployment and total technological change.

The reason for excluding unemployment form the analysis so far is that technological age increases per occupation due to technological change as captured by the *BIBB Data*. Alas, naturally there is no possibility to measure technological change for unemployment. Thus, there is no way to know how technological age should change for workers being unemployed or workers becoming unemployed. Therefore, it is not only impossible to include unemployed workers in the regression for the time they are unemployed as their technological age would not change and would not play a part in the person fixed effects model. Workers coming out of unemployment can also not be used, as it is not possible to know the change in technological age they should experience coming out of unemployment into a certain occupation. To remedy the problem of not knowing how technological age changes during unemployment, this section does not include the unemployed observations in the analysis but rather only counts changes into unemployment in the next period as an occupation change in the next period. In short, the only difference between the regression in Section *8.1* and here is that not only future occupation changes to other occupations are relevant for the dependent variable but also changes into unemployment in the next period.

As can be seen in *Figure 35*, including change into unemployment does not alter the results much. Including the change to unemployment seems to have increased the likelihood to leave an occupation due to technological age slightly but not by much. The overall trend in marginal effects is very similar when comparing regressions with and without unemployment. Especially the occupations with an already higher likelihood of workers leaving due to technological age have further increased the likelihood to change the occupation due to technological age when including changes into unemployment. The trend that occupations with less overall technological change are impacted more by technological age is further strengthened by including the possibility to change into unemployment into the regression analysis. This finding is also supported by *Figure 36*, showing the likelihood to change occupation due to technological age on the y-axis and the total technological change per occupation in the x-axis. The marginal effects of occupations with lower technological change are increased while the marginal effects for the occupation with more technological change are not impacted as strongly. The overall negative correlation between the likelihood to leave an occupation due to technological age and total technological change per occupation is still visible. This correlation is furthermore very similar between regression (5), not using unemployment with -0.6580, compared to -0.4918 for the regression including unemployment as *Table 22* shows.

Overall, adding the possibility for workers to become unemployed into the analysis does not change the results much. The trend that Hypothesis 3 fits better for workers in occupations with less technological change is strengthened a little; the overall results do not change. The next section discusses further possible robustness measures such as extending the timeframe of the analysis using the *KldB2010* and imputing starting technology for workers starting to work before 1979.

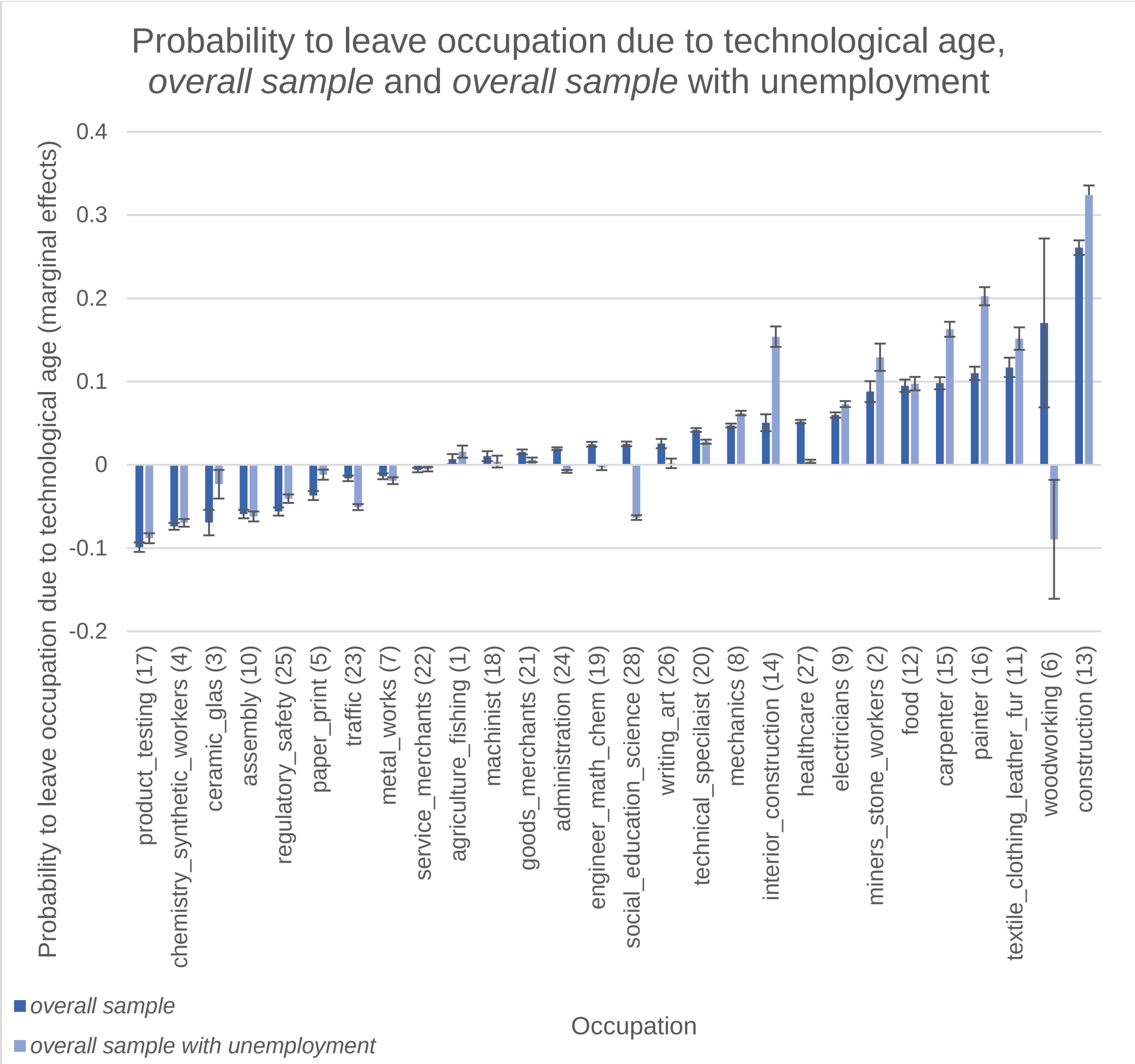

Figure 35: *Probability to leave occupation due to technological age, overall sample and overall sample with unemployment*

Note: Marginal effects of regression (5) and regression (22), ordered by size of marginal effects in regression (5) including standard errors. Regression (5) and (22) can be found in Table A64.

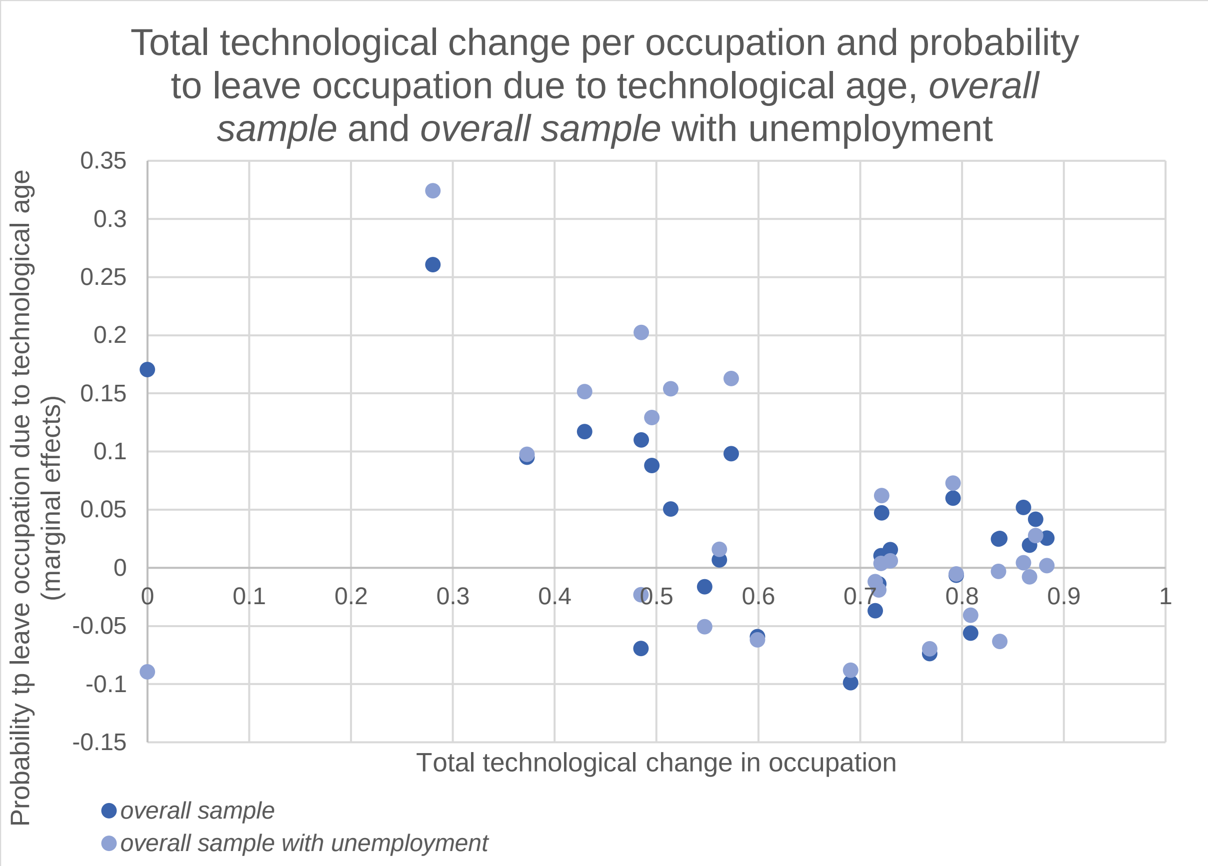

Figure 36: *Total technological change per occupation and probability to leave occupation due to technological age, overall sample and overall sample with unemployment*

Note: Marginal effects of regression (5), regression (22) and overall technological change per occupation from Table A11 to Table A15. Regression (5) and (22) can be found in Table A64.

Table 22: *Linear correlation between the marginal effects of regression (5), regression (22) and technological change per occupation*

Correlation between	Sample Period	Correlation
marginal effects likelihood to leave occupation technological change	*overall sample* *overall sample*	-0.4918
marginal effects likelihood to leave occupation with unemployment technological change	*overall sample* *overall sample*	-0.6580
marginal effects likelihood to leave occupation marginal effects likelihood to leave occupation with unemployment	*overall sample* *overall sample*	0.9156

Note: The correlation does not include the observation for woodworking (6).

9.4 Further robustness checks

This section lists two more possible robustness checks and discusses them, namely using the *KldB2010* to extend the sample period and imputing starting technology for workers who started to work before 1979. As already described in Section *7.3*, using the *KldB2010* it is possible to extend the *overall sample* up to the year 2012, adding six years to the sample period. This extended sample period could then be used to test for robustness when it comes to the years after 2006 while Section *4.2 Regression model wage analysis* and Section *5.2.1 Data description SIAB Data* talk about the problems regarding starting technology.

As the robustness checks established the results between using the *KldB88* and using the *KldB2010* occupation classifications to be slightly different from another, it would be telling to see whether the results are also robust for the years 1979-2012. Alas, since the last subsample, *subsample 00*, was not as robust as the other subsamples when comparing *KldB88* and *KldB2010*, this volatility comes into play when extending the *overall sample* to 2012. Estimating a regression while extending the sample period to 2012 yields vastly different results compared to the *overall sample* regression. In fact, the marginal effects become overall much more negative, meaning that technological age makes workers more unlikely to leave their occupation due to technological age. The full output tables for the extended sample regression can be found in Appendix *A15.iv*. Furthermore, the correlation between the likelihood to leave an occupation due to technological change and total technological change experienced differs when extending the sample period. In the *overall sample*, the correlation between the likelihood to leave an occupation due to technological age and total technological change per occupation was -0.4918[77] while for the extended sample of 1979-2012 the correlation is 0.5566[78]. Even though this is a stark difference, these results are much more similar to the results of regression (8) where the *KldB88* was used on the *subsample 00*. For regression (8) there were also more negative marginal effects and the correlation between the likelihood to leave an occupation due to technological age and the total technological change per occupation was 0.3904[79]. Overall, there

[77] See *Table 17* for reference.
[78] *Table A65: Linear correlation between the marginal effects of regressions (18), (22) and (8) and technological change per occupation* can be found in Appendix *A15.iv*.
[79] See *Table 19* for reference.

seem to be some changes in the way technological age affects a worker's decision to leave an occupation towards the end of the same period and the results are not as robust as the results from the earlier parts of the sample period.

Another way to check for robustness would be to impute the starting technological age for everyone starting to work before the start of the dataset in 1979. The same problems regarding the starting technology as discussed in Section *4.2* and Section *5.2.1* are applicable here, namely assuming that the starting technology for everyone who started working before 1979 is the same technology that was prevalent in each occupation in 1979. Similar to Section *7.3,* the starting technology for entry into the labor force before 1979 was imputed assuming a linear trend in technological change in each occupation and following this trend backwards until the starting technology is zero for each occupation. This imputed starting technology is then added into the data, potentially changing the technological age of workers who started to work before 1979. Again similar to Section *7.3*, imputing starting technology does not change the results much at all, as can be seen in Appendix *A15.v*. Naturally, this makes sense as the person fixed effects regression only takes yearly changes in technological age into account and the yearly technological age progression does not change with a different technological level at the entry point into the labor market.

Overall, the results of regression (5) seem to be rather robust to changing occupation classification or imputing new starting technological ages. Only extending the sample period is problematic as well checking for robustness towards the end of the sample period. In the later years, results do not seem to be robust, and the robustness checks are more volatile. The next section provides a joint viewpoint on the results of the wage and occupation change effects of technological age and shows the overall impact of technological age on workers.

10 Combining wage analysis and occupation change analysis results

First, this section gives a short overview over the results of the wage and the occupation change analysis. So far, there have been separate analyses for Hypothesis 2, that technological age decreases worker’s wages and Hypothesis 3 that technological age makes workers more likely to change occupations. Hypothesis 2 and 3 both exist to show how the depreciation of technological specific human capital can affect workers as stated in Hypothesis 1, namely that technological age makes workers less efficient when using new technologies and because Hypothesis 1 could not easily be proven on its own. While the analysis of the influence of technological age on wages proved Hypothesis 2 for most occupations, the results are not completely straightforward. Across the entire sample period, technological age only decreases the wage of workers in most occupations but not for workers in all occupations. In some occupations, technological age leads to an increase in wages. However, when splitting the sample into different subsamples, it becomes clear that in *subsample 79* and even more so in *subsample 90*, technological age had a mostly positive effect on wages. Only in a few occupations did technological age lead to a decrease in wages. This result is vastly different for *subsample 00* where technological age decreased wages for workers in every occupation. Thus, it does seem like technological age had a negative impact on wages in *subsample 00* but not as much in the years before. Furthermore, in *subsample 79* and *subsample 90*, occupations with less technological change experienced in the timeframe are affected more by technological age while this trend all but disappears in *subsample 00*.

The analysis of how technological age affected the probability of workers leaving an occupation also proved Hypothesis 3 true for most occupations, yet the results must be analyzed in a more differentiated fashion. Across the *overall sample*, technological age increases the probability for workers to leave their occupation in most occupations. Similarly to the effect of technological age on wages, in some occupations technological age decreases the likelihood of workers to leave. When looking at the influence of technological age on the probability to leave an occupation in the subsamples, the results differ. In *subsample 79* and *subsample 90,* technological age made workers more likely to leave their occupation in almost all occupations; otherwise, technological age had no effect regarding workers leaving their occupation. In *subsample 00*, technological age made workers in most occupations more likely to stay in their occupation. Thus, technological age increased the likelihood of workers leaving their occupations in the years 1979-1999 but mostly decreased the likelihood of workers leaving their occupations in the years 2000-2006. Furthermore, in *subsample 79* and *subsample 90* occupations that have experienced less technological change in the respective time periods have a higher likelihood of workers leaving due to technological age than occupations with more technological change in these time periods. As in the wage analysis, this trend is reversed for *subsample 00,* where occupations that have experienced more technological change during the subsample have an increased likelihood of workers leaving because of technological age.

In order to have a more complete picture of the influence of technological human capital depreciation on workers, the effects of technological age on wages and on the likelihood to leave an occupation should be analyzed simultaneously. When analyzing the effect of technological age on wages and the effect of technological age on the probability to change occupations, two things are apparent:

1. The negative influence of technological age on wages and the increase in likelihood to leave an occupation due to technological age are prevalent in different time periods.
2. The same occupations that are more affected by the wage effect of technological age are also the occupations where technological age has a greater impact on the likelihood of workers leaving the occupation.

First, when looking at the subsamples the negative influence of technological age on wages and the increase in likelihood to leave an occupation due to technological age are prevalent in different time periods. As stated above, during the earlier years of the *overall sample*, i.e., *subsample 79,* there are very few occupations with a negative impact of technological age on wages, yet workers in every occupation are more likely to leave due to technological age. During the middle part of the *overall sample*, i.e. *subsample 90,* there were even less occupations in which workers were receiving a wage decrease due to technological age, yet still technological age made workers more likely to leave their occupations across the board. During the last years of the sample period, *subsample 00,* workers in every occupation received a wage malus due to technological age but were less likely to leave their occupations due to technological age.

Alas, the analysis does not make it clear why the effects are distributed in this fashion, a reason for this change in impact of technological age cannot be given by this analysis. Yet, this analysis gives a hint for what to look out for when further analyzing the influence of technological age on workers. It is possible that in the beginning of the sample workers were running away from the wage decrease or were being forced to leave due to technological age, while at the end of the *overall sample,* workers simply took the wage decrease and did not leave their occupation anymore. It is also possible that the nature of technological change transformed in a way that the impact of technological age on workers changed as well. Alas, any explanation for the different impact of technological age across time is pure speculation. What can be said with a degree of assuredness, however, is that the wage effect and the occupation change effect of technological age appear in different time periods. At the beginning of the *overall sample,* Hypothesis 3 is proven, technological age makes workers more likely to leave their occupation, while only very few occupations also experience a wage malus due to technological age, making Hypothesis 2 mostly unproven for this timeframe. Furthermore, it is not possible to know whether the positive impact of technological age of wages outweighs the negative impact of technological age on the probability to change occupations. Therefore, Hypothesis 1 cannot be proven overall for the years 1979-1999. Towards the end of the *overall sample,* Hypothesis 2 can be proven; technological age negatively affects wages in all occupations. At the same time, technological age is only increasing the likelihood of workers to leave in some occupations, making it not possible to prove Hypothesis 3. Yet the fact that there is a negative impact of technological age on wages across the board during the *subsample 00* makes it easier to discern an overall impact of technological age on workers. Workers receive less wages due to technological age in every occupation but are less likely to leave an occupation due to technological age. The fact that workers do not leave their occupations due to technological age does in no way remedy the negative wage effect, making it clear that technological age makes workers less efficient when using new technologies. Thus, Hypothesis 1 can be proven for *subsample 00*.

Bullet point number two above mentions that the same occupations that are more affected by the wage effect of technological age are also the occupations where technological age has a greater impact on the likelihood of workers leaving the occupation. In other words, there is a negative correlation between the size of the marginal effects of the wage analysis and the size of the marginal effects of the occupation change analysis. The correlation between the marginal effects of the wage and occupation change analysis can be found in *Figure 37*[80] for the entire sample period as well as *Figure 38* to *Figure 40* for the subsample time periods. Furthermore, the linear correlations of the marginal effects of the wage and occupation change analysis can be found in *Table 23* to help to quantify the correlations again. The negative correlations between the size of the marginal effects of the wage analysis and the size of the marginal effects of the occupation change analysis show that the occupations that have their wage more negatively affected by technological age are also the same occupations where technological age increases the likelihood of a worker to leave their occupation the most. The occupations that are not affected by the wage effect of technological age as much are also the occupations where workers are less likely to leave due to technological age. In fact, not only do *Figure 37* to *Figure 40* show a clear negative correlation between the size of the marginal effects of the likelihood to leave an occupation and the marginal effects of the wage impact of technological age, *Table 23* reinforces this notion. For the *overall sample*, the correlation between the occupation change and wage impact of technological age is -0.4806, for *subsample 79, subsample 90* and *subsample 00* the linear correlations are -0.8274, -0.6615 and -0.5273 respectively, showing how clear the relationship between occupation change and wage impact of technological change really is.

This could lead to the conclusion that workers might leave their occupations to preempt or mitigate the wage effect of technological age, yet, as discussed above, the wage and occupation change effects of technological age largely appear in different time periods, with the negative wage effect appearing after the increase in likelihood to change occupations. Rather than the option that workers leave their occupation due to the wage effect of technological age, one has to entertain the idea that the same kind of occupations are more negatively affected by both, the wage effect of technological age and the occupation change effect of technological age. The analysis so far

[80] The figures can be found at the end of the section.

suggests that during *subsample 79* and *subsample 90*, it is mostly the occupations which experienced less technological change in subsample that are more negatively affected by technological age. Occupations with less technological change in this timeframe are both more negatively affected by the wage and the occupation change channel of technological age.

Alas, the same is not true for *subsample 00*. The analysis so far suggests that it is not the occupations that experienced a lot of technological change during this subsample that ore more negatively affected by technological age. Yet, this finding is due to the fact that the analysis so far has only looked at the technological change per occupation during the subsample period. When looking at the correlation between the wage impact of technological age in *subsample 00* and the technological change per occupation across the *overall sample*, the correlation becomes similar to the correlations in *subsample 79* and *subsample 90*. The same is true for the impact of technological age on the probability of a worker to leave an occupation in *subsample 00* and the technological change per occupation across the entire sample period. The reason why it makes sense to look at the *overall sample* technological change rather than technological change per time period in *subsample 00* is that some of the most technologically intensive occupations had already reached 100 percent computerization before 2006 and thus did not have a lot of measured technological change happen during *subsample 00*. As can be seen in Section *5.1.4 Technological progression according to BIBB Data*, technological change cannot be measured in these occupations any longer, as they achieved one hundred percent computerization. Yet it is rather preposterous to think that no technological change took place during *subsample 00* in the occupations that were the first to fully utilize computer technology. Rather, this leads back to the weaknesses of the chosen measure of technological change. Thus, when comparing occupations based on the technological change they encountered, using technological change per subsample might yield skewed results for *subsample 00*.

Figure 41 shows the marginal effects of the *subsample 00* wage and occupation change analysis alongside the technological change per occupation from the *overall sample*, while *Table 24* shows the correlation coefficients between the marginal effects of the *subsample 00* wage and occupation change analysis and the total technological change per occupation during the *overall sample*. The graph and the correlation coefficients make it clear that it is still the occupations with the less overall technological change that are being hurt by the wage and occupation change effect of technological age, just as in the years before. This becomes especially apparent when looking at the linear correlations in *Table 24.* The correlation between the wage impact of technological age and overall technological change per occupation is now clearly positive with 0.7656, while the correlation between the likelihood to leave an occupation due to technological age and overall technological change per occupations is now clearly negative with -0.6857. These correlations are much more similar to the correlations of *subsample 79* and *subsample 90* in the wage and occupation change analysis[81]. Thus, while towards the end of the *overall sample* technological age seems to affect wages much more negatively than technological age affects the likelihood of workers leaving their occupations, the occupations that experienced less technological change overall are affected more negatively by technological age throughout the entire analysis compared to occupations that experienced more technological change overall.

To sum up the overall effect of technological specific human capital depreciation as stated in Hypothesis 1, technological age makes workers less efficient when using new technologies. Alas, as always reality is not that simple. This analysis makes it clear that most occupations show a negative effect of technological age on wages and an increase in the likelihood to leave an occupation due to technological age across the *overall sample*. Thus, for most occupations, Hypothesis 2 and Hypothesis 3 are proven for the *overall sample* period. For other occupations however, Hypothesis 2 and Hypothesis 3 cannot be proven. When looking at the subsamples, a more differentiated picture emerges. The analyses from the subsamples show that at the beginning of the *overall sample*, Hypothesis 3 is true; the influence of technological age on the probability to leave an occupation is much stronger. However, the overall impact of technological age is offset by the fact that many occupations pay more wages due to technological age. Therefore, Hypothesis 1 cannot definitively be proven. Towards the end of the *overall sample,* Hypothesis 2 is proven; technological age has a negative impact on wages in all occupations. During *subsample 00*, workers are also more likely to stay in their occupations due to technological age, making the wage effect of technological age potentially even more difficult for workers. Furthermore, the results of the occupation change analysis were not very robust in *subsample 00*, making it difficult to pinpoint the true impact of technological age in the timeframe. Thus, the impact of

[81] The linear correlations can be found in *Table 13* and *Table 19*.

technological age is negative towards the later years of the *overall sample* and Hypothesis 1 can be proven. Even though the way technological age impacts workers changes during the *overall sample*, the occupations most hurt by technological age stay the same. The occupations that experience less overall technological change are always affected more negatively by technological age when compared to occupations that experienced more technological change.

The next section discusses the results further as well as discussing potential problems of the analysis and further research that has to be done. The focus is on possible issues regarding the measurement of technological age as well as potential problems arising from the empirical models employed for this analysis.

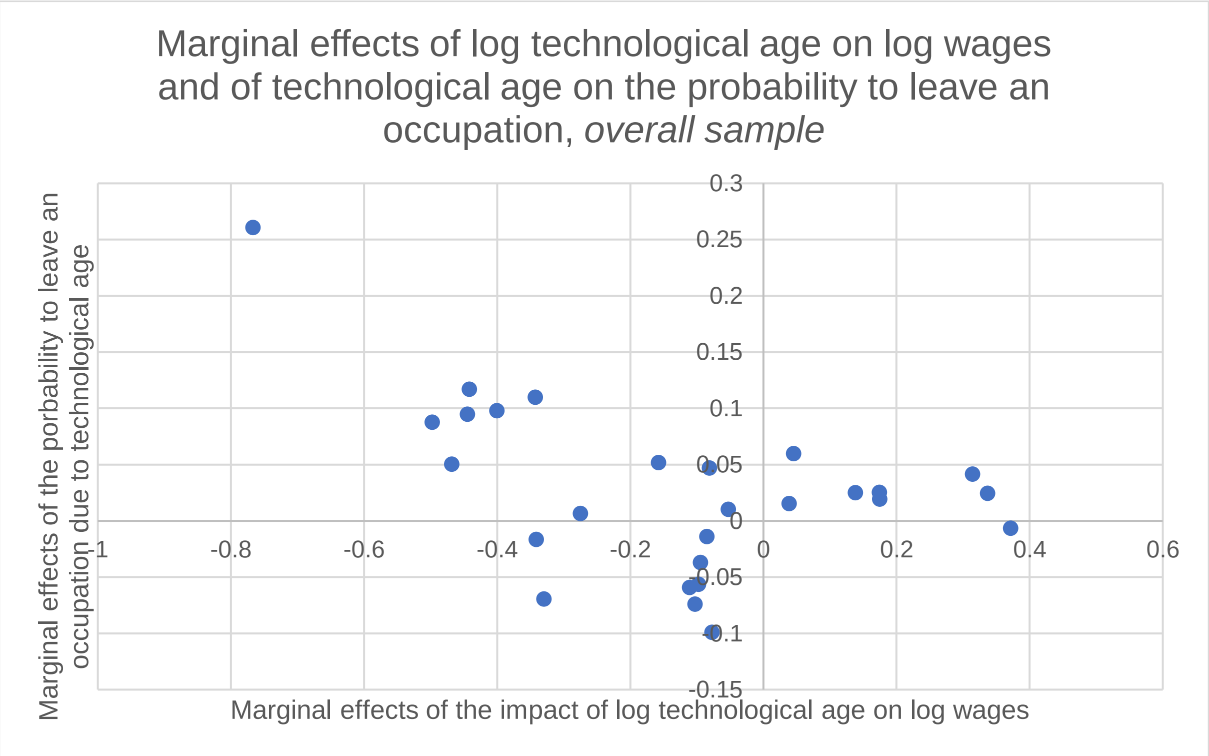

Figure 37: *Marginal effects of log technological age on log wages and of technological age on the probability to leave an occupation, overall sample*

Note: Marginal effects of regression (1) on the x-axis and marginal effects of regression (5) on the y-axis. Regression (1) and (5) can be found in Table A52 and Table A60.

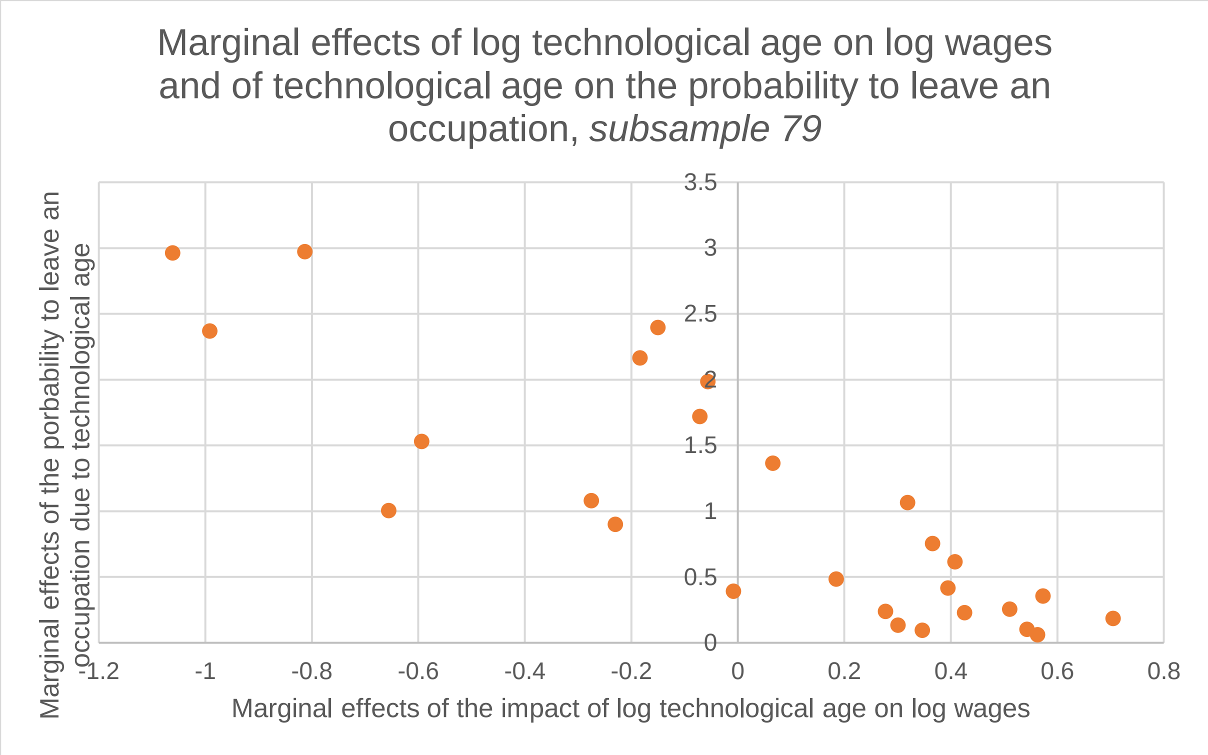

Figure 38: *Marginal effects of log technological age on log wages and of technological age on the probability to leave an occupation, subsample 79*

Note: Marginal effects of regression (2) on the x-axis and marginal effects of regression (6) on the y-axis. Regression (2) and (6) can be found in Table A53 and Table A61.

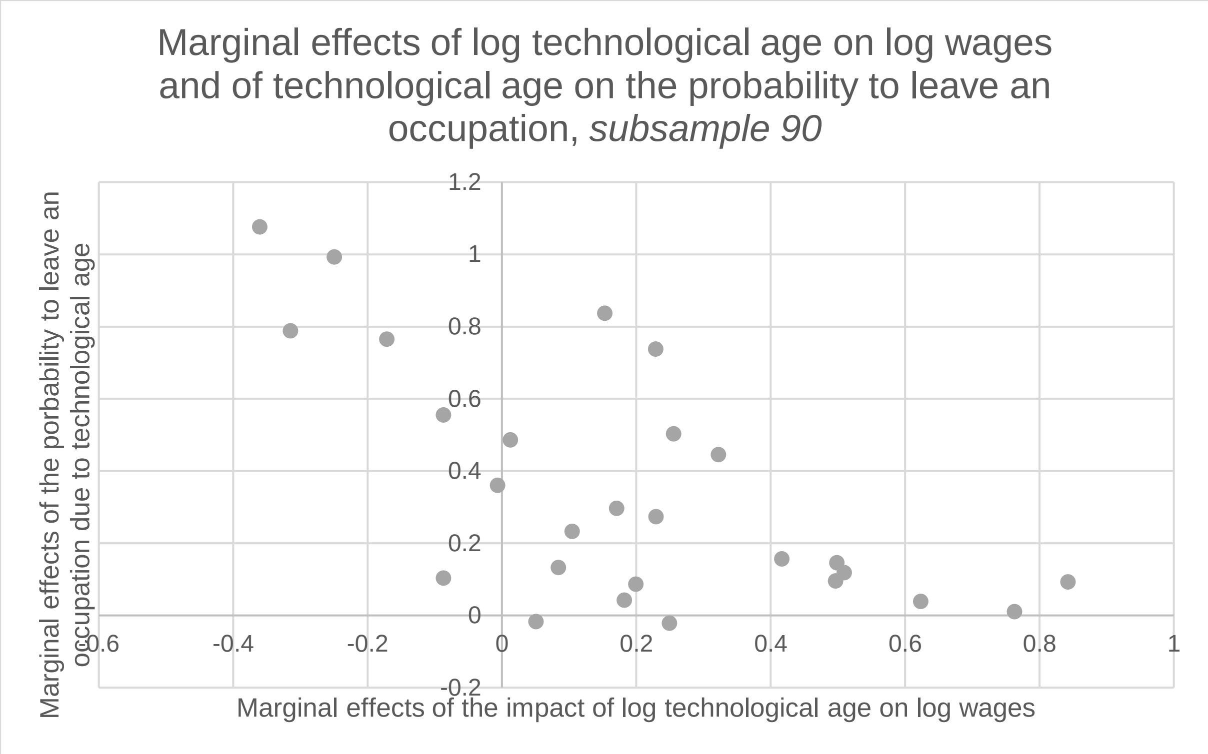

Figure 39: *Marginal effects of log technological age on log wages and of technological age on the probability to leave an occupation, subsample 90*

Note: Marginal effects of regression (3) on the x-axis and marginal effects of regression (7) on the y-axis. Regression (3) and (7) can be found in Table A53 and Table A61.

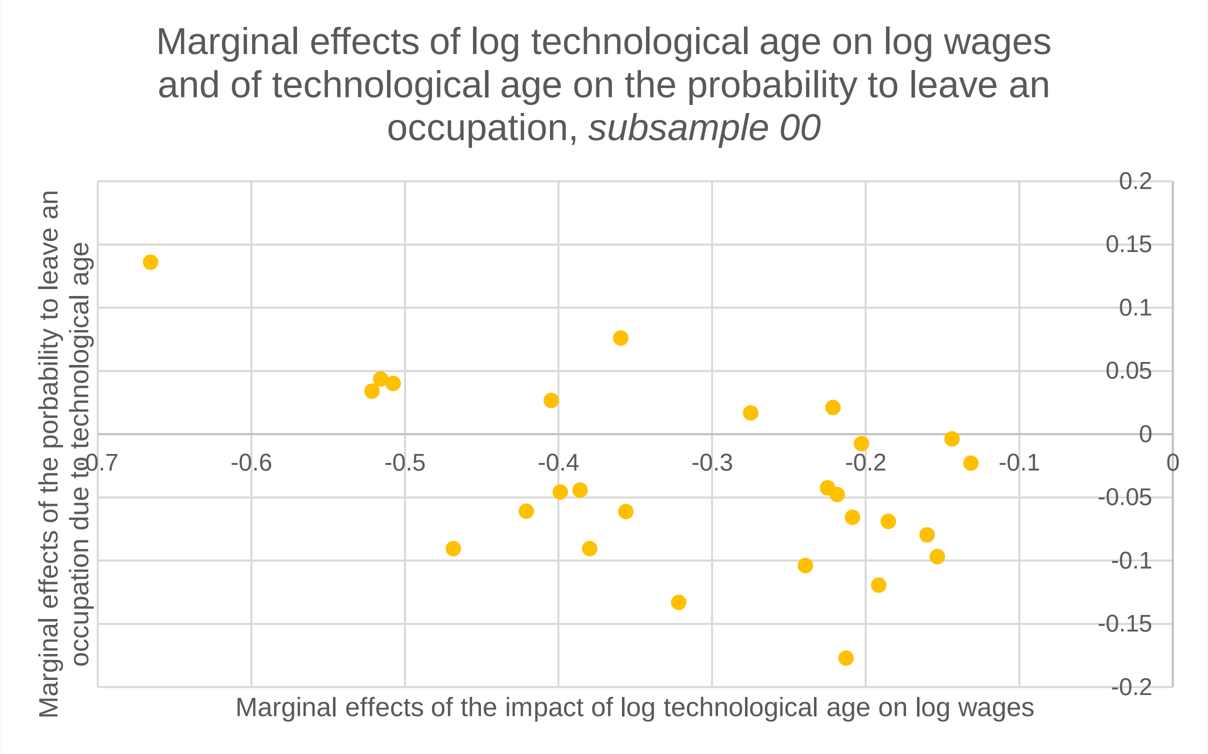

Figure 40: *Marginal effects of log technological age on log wages and of technological age on the probability to leave an occupation, subsample 00*

Note: Marginal effects of regression (4) on the x-axis and marginal effects of regression (8) on the y-axis. Regression (4) and (8) can be found in Table A53 and Table A61.

Table 23: *Linear correlation between the marginal effects of the wage regressions (1)-(4) and the marginal effects of the occupation change regressions (5)-(8)*

Correlation between	**Sample Period**	**Correlation**
marginal effects wage impact (1) marginal effects likelihood to leave occupation (5)	*overall sample* *overall sample*	-0.4806
marginal effects wage impact (2) marginal effects likelihood to leave occupation (6)	*subsample 79* *subsample 79*	-0.8274
marginal effects wage impact (3) marginal effects likelihood to leave occupation (7)	*subsample 90* *subsample 90*	-0.6615
marginal effects wage impact (4) marginal effects likelihood to leave occupation (8)	*subsample 00* *subsample 00*	-0.5273

Note: The correlation does not include the observation for woodworking (6).

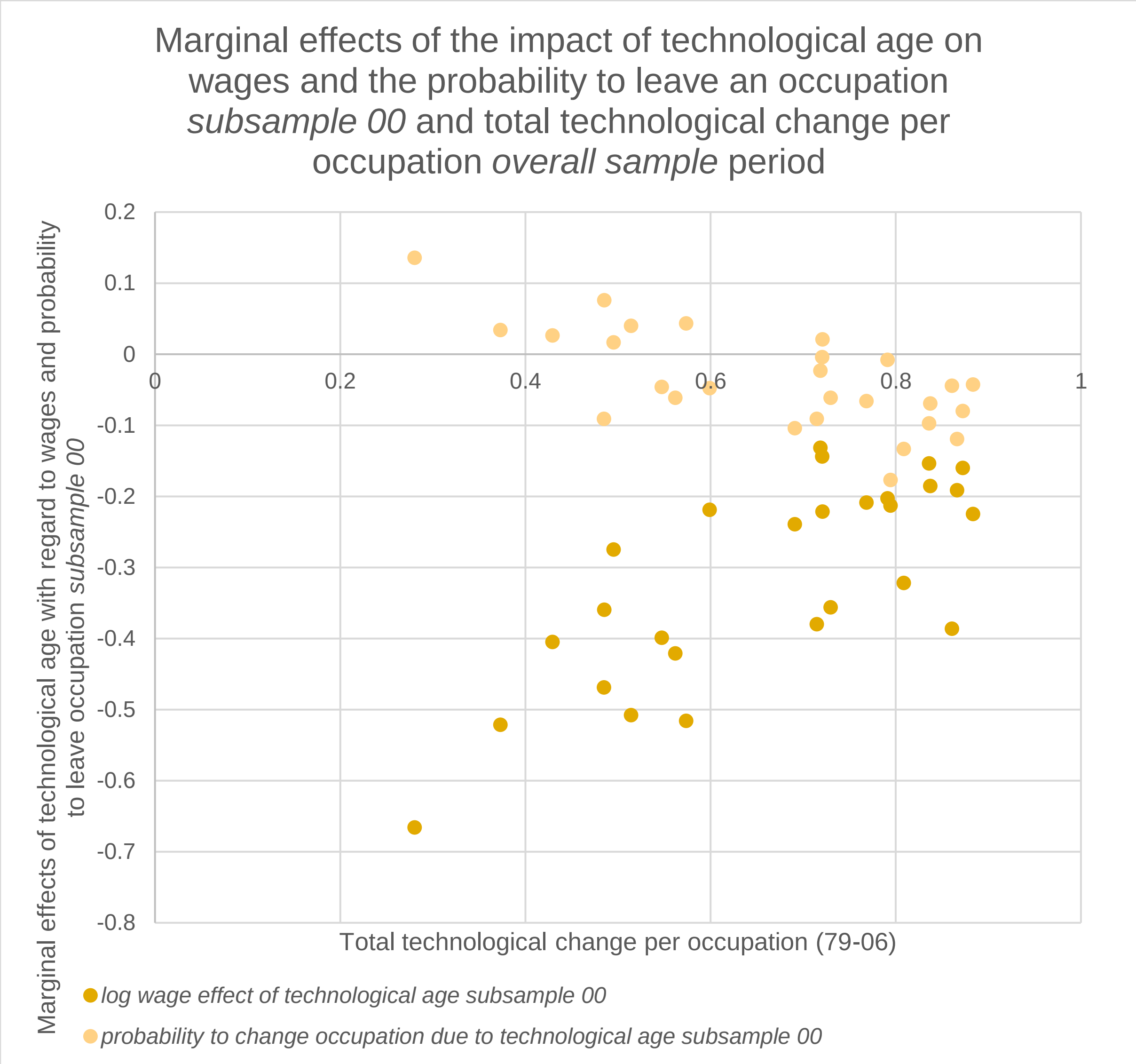

Figure 41: *Marginal effects of the impact of technological age on wages and the probability to leave an occupation subsample 00 and total technological change per occupation overall sample period*

Note: Technological change per occupation in the overall sample period according to Table A3 to *Table A6 on the x-axis and marginal effects of regression (4) and regression (8) on the y-axis. Regression (4) and (8) can be found in Table A53 and Table A61.*

Table 24: *Linear correlation between the marginal effects of regression (4), regression (8) and technological change per occupation during the overall sample*

Correlation between	Sample Period	Correlation
marginal effects wage impact	*subsample 00*	0.7656
technological change	*overall sample*	
marginal effects likelihood to leave occupation	*subsample 00*	-0.6857
technological change	*overall sample*	

Note: The correlation does not include the observation for woodworking (6). Regression (5) and (8) can be found in Table A53 and Table A61.

11 Discussion

This section discusses some potential shortcomings and problems of the analysis. As with every analysis and every research, this analysis has some shortcomings that are important to keep in mind and some areas where further research could improve the understanding of the topic or where further research might be necessary to analyze the problem further. It is always important to have an overview of these potential problems or the need for further research. Thus, this section considers potential problems or shortcomings and for this purpose, mainly focuses on two areas of the analysis where there are potential problems, or the analysis could be improved:

1. The measurement of technological change and resulting problems in the estimation of technological age.
2. Problems with the empirical models and potential miss estimation or misinterpretation of the resulting marginal effects of technological age on wage or occupation change.

11.1 The measurement of technological change

The first area holding potential weaknesses is the measurement of technological change and the subsequent estimation of technological age. Section *5.1.1 Measuring technological change* has already alluded to the fact that much of the analysis rises and falls with the correct measurement of technological change and the resulting translation of technological change to individual technological age. The two main problems discussed are the use of computer usage per occupation for measuring technological change with the resulting weaknesses and the lack of training in the analysis with the resulting impact on the correct estimation of technological age and the interpretation of the results.

The potential problems with measuring technological change as change in computer usage per occupation should be discussed again in more detail than in Section *5.1.1*. The first potential problem that arises is that even though the wage and occupation changes are measured on an individual level, technological change happens on an occupational but not an individual level. The model therefore uses occupation wide data to determine individual outcomes, which might lead to problems. The drawback in measuring technology change on an occupational level is that technology changes similarly for each employee in an occupation, regardless of whether or not there were any actual changes in technology for the individual employee. This means that even though computerization changed across the occupation, some employees might not have seen any technological change happen to their work. Even though overall the occupations keep adding more and more computers, some workers are still not working with computers and thus should have no technological age. For the individuals not working with a computer at all, technological age could be overestimated while for individuals working with a computer early on in the sample the technological age could be underestimated. Alas, individual technology use was impossible to show in the data and thus it was not possible to create a truly individual technological age progression. For the purpose of this analysis, the occupation wide estimation of technological change and technological age probably was not a huge problem as the data utilized a large sample of individuals, reducing the risk of grossly miss estimating technological age for most workers. Alas, ideally, one could create a measure of technological age based on the tasks a worker completes leading to an individual technological age measure. If such data were available, it would be interesting for further research to estimate the impact of individual technological age on workers.

Another already shortly mentioned problem[82] is the use of computers as a proxy for technological change. While computer usage is widely used in the literature to measure technology or technological change[83], it has some obvious drawbacks, both in general and for this analysis in particular. Of course, it is immediately obvious that computer usage leaves out many technological advances, especially automation in manufacturing and other technological machines in healthcare. In many occupations, workers use technologies other than computers very intensively and thus have larger technological ages than estimated simply by computer usage. Alas, not only does using computer usage for the measurement of technological change leave out many technology users, it also stops being useful as a scale for technological change once computers are used everywhere. This could have been especially problematic in the

[82] Theis problem was already mentioned in Section *5.1.1*.
[83] Papers that use computers are example as cited in Section *5.1.1:* Autor, Katz and Krueger (1998), Card and DiNardo (2002) and Spitz-Oener (2006).

later years of the analysis as many occupations were at one hundred percent computer usage before the end of the sample period. Yet, it is ridiculous to think that these occupations stopped having technological change, rather the nature of technological change was different. Changes in computer programs, software used and the implementation of the internet with including changes in computer utilization are not captured by change in computer usage. This fact probably led to the underestimation of technological ages in several occupations, especially towards the end of the sample period. Alas, similarly as above, the best solution to the underestimation due to computer usage being the technological change measure would be to create a measure of technological age based on the tasks a worker completes. Not only could the impact of true personal technological age be estimated, but it might also be possible to move beyond the simple measure of computer use and look at the complexity of computer usage, the amount of computer usage, changes in computer programs or the usage of other technologies or automated machines. If possible, further research using a truly individual and comprehensive way to measure technological age would be the best way to gain further insight into the impact of technological age on wages.

The last potential issue with the measure of technological age in this analysis is the absence of training in the data used in this analysis. It is theoretically possible, that training can decrease human capital depreciation and thus training could have had a major impact on the real technological age of workers. This argument is also in line with the third strand of literature in Section *2, Literature,* where Behaghel, Caroli, and Roger (2014) and Schleife (2008) find that training can improve the employment prospects of older workers in innovative firms. Furthermore, it is possible that training employees could lead to a reversal of the human capital depreciation caused by technological age. In this case, occupations intensively training their employees would increase the human capital of their workers more than the human capital would decrease due to technological change and the measured technological age variable would in turn show the increased human capital[84]. Of course, training was not part of the data and could therefore not be part of the model. Additionally, Heß et al (2019) and Lukowski et al (2020) suggest that occupations using more technology are more likely to train

[84] While a lot of research on human capital depreciation exists, for example Arrazola and Hevia (2004), Arrazola et al (2005), Bapna et al (2013), Hanushek et. al. (2017), Kunze, (2002) McFadden (2008), Mincer and Ofek (1982) and Weber (2014), the focus is not on whether training can reverse the potential personal human capital depreciation of technological change.

their employees. Since the occupations with a positive effect of technological age on wages were also the occupations with the most technological change overall, it is not unlikely that the positive wage effect of technological age stems from the effect of training on human capital. Furthermore, if technologically intensive occupations do train their workers better or more often, workers in the technologically intensive occupations might not want to leave their occupation in order to reap the returns of their investment into training. Training could therefore also be a reason that workers are less likely to leave technologically intensive occupations due to technological age. In fact, training in more technologically intensive occupations and the lack of training in less technologically intensive occupations might be a large part of the reason why occupations with less technological change seem to be affected more negatively by technological age.

According to Ahituv and Zeira (2011), trained workers are also less likely to leave their occupations for early retirement. If indeed occupations with less overall technological change train their workers lees frequently, the finding that workers are more likely to leave less technologically intensive occupations compared to high technologically intensive occupations might be underestimated. Workers in less technologically intensive occupations might be hurt more by technological age than shown by the occupation change analysis as changing occupations into early retirement is not part of the data. Showing the role training could have on the way technological age influences workers should be the goal of further research and might shed further light on why some occupations are more affected by technological age than others are.

In summary, the way technological age is measured leads to potential problems in the estimation of technological age in the analysis. The utilization of computer usage as technological change, while common in the literature, leads to potentially underestimating technological age in occupations that utilize technology differently than in the form of computers. The utilization of computer usage as technological change also bears problems for the highly computerized occupations in the later years where it does not capture the ongoing change in computerization any longer and thus probably leads to an underestimation of technological age in occupations strongly utilizing technology. Finally, the absence of training in the analysis could also lead to a miss estimation of technological age, especially an overestimation of technological age in the highly technology using occupations. Especially the underestimation of technological age in highly technologically intensive occupations due to computer usage not changing in the later years and training being absent in the dataset might account for some of the results showing technological age being more detrimental to the lower technology intensive occupations. While the results of this analysis provide a good starting point into analyzing the impact of the novel concept of technological age, better data and especially more individual data on technology use would be useful to gain a better understanding of technological age and its impact on workers. Alas, the measurement of technological age is not the only problem worthy of discussion. There are also some points related to the used empirical models that are discussed in the next section.

11.2 The empirical models

The second area where there are potential further thoughts needed are the empirical models of the wage and occupation change analyses. Several points are discussed in further detail. For one, the models all assume the effect of technological age on wages and the effect of technological age on the probability to change an occupation to be constant across the entire sample period or sample-sub-period in the respective regressions. Furthermore, as technological age changes similarly for all employees of an occupation from year to year, it might capture yearly occupation specific effects in the empirical models. Both issues could lead to a misestimation of the marginal effects in the empirical models. Additionally, one of the greatest weaknesses of linear probability models is the possibility of estimating marginal effects above one. In this analysis, the linear probability models estimate marginal effects above one when there is little technological change. Alas, while the analysis estimates the impact of technological age on the probability to leave an occupation, the analysis does not show into which occupations these workers change. This naturally weakens the analysis on occupation change and is debated in more detail. Finally, the fact that the wage analysis uses a log-log model, and the occupation change analysis uses a linear probability model could lead to misinterpretation of the effects of technological age when comparing the marginal effects within each model and when comparing the marginal effects of both models with each other.

The first potential issue with the empirical models is the assumption that the impact of technological age on both, wages and the probability to change occupation, is constant across time. If the influence of technological change differs strongly over time, the regressions simply give an overall effect for the whole sample period without showing the nuanced impact technological change could have during different timeframes. More clearly, the regression gives a sort of average effect of technological age across the sample period that lacks insight into what happened at different times. Alas, the regressions of the sub samples give results that differ widely from the results of the regressions using the entire sample period, pointing towards the possibility that the effects of technological age on wages and the probability to change occupations are not constant over time. On the other hand, the sub sample regressions give an insight into the influence of technological age in the different time periods. Yet, as the impact of technological age per time period differs widely, more research into the impact of technological age on wages and the impact of technological age on the probability of a person changing occupations in different time periods might be necessary.

Secondly, due to the nature of measuring technological change on an occupational level, technology changes by the same amount each year for every worker in the same occupation. Therefore, the way technological change is measured could also lead to some technical problems for the regressions. Since the regression models are estimated as person fixed effects models, only the change in technological age each year plays a role for estimation in the model. As the change in technological age is the same for all workers of each occupation each year, this variable could capture occupation specific, yearly effects. In short, the technological age variable, due to being measured in occupation specific, yearly technological age changes, could act as a sort of occupation specific year fixed effect, capturing shocks to the occupation and therefore overestimating the impact of technological age. For example, if there was a shock in the agriculture occupation that could have led to lower wages, such as bad weather, that did not affect other occupations in the same year and therefore did not get captured in the year fixed effects, this shock could be captured in the occupation specific technological age variable. Naturally, the model utilizes control variables to lessen the possibility of omitted variable bias by including year fixed effects and a change in employment variable, capturing changes in employment in the occupations. Yet, due to the nature of measuring technological change, it is impossible to include occupation specific year fixed effects. While it is unlikely that each occupation experienced continuous circumstances that were specific to each occupation and could not be captured by occupation specific business cycles, it is important to keep in mind that the technological age variable could at times include other occupation specific effects. However, the problem of not being able to include occupation specific year fixed effects into the regressions still comes back to the fact that the data did not allow to measure technological age on a truly individual level. Similarly to Section *11.1*, if there was the possibility to estimate individual technological ages, further research might prove insightful.

Other possible problems to keep in mind have largely to do with the linear probability model used to describe the impact of technological age on the probability to leave one's occupation. It is widely known that linear probability models can estimate coefficients above one, which cannot be true. In this analysis, especially the regressions from *subsample 79* and to a lesser extent the linear probability models estimated for the *subsample 90* have this problem. As already mentioned in Section *8.4* and Section *9.2*, this might not necessarily be overly problematic in the case of the subsample regressions, as the amount of technological age change was very small for many occupations, especially during *subsample 79*. Thus, the impact of the actual technological change was still being reasonably estimated by the model and for the technological age that happened in the timeframe, the coefficients are not necessarily wrong. Alas, the simple fact that the linear probability models estimated effects above one shows that there are always potential problems when working with linear probability models. As mentioned in Section *4.3 Regression model occupation change analysis*, there are no easy solutions when working with binary models in a panel setting. For example, the fixed effects logit makes it impossible to estimate average partial effects as well as partial effects on the response probabilities[85] and thus makes it difficult to use for comparison with the wage analysis[86].

Another shortcoming related to the occupation change analysis is that while it is possible to show that technological age has an effect on whether workers leave their occupations, it is not possible to show whether the workers leaving their occupations

[85] Wooldridge (2010), pp. 490 ff.
[86] A further possibility to remedy the potential problems using linear probability models in a panel setting bring is to use a correlated random effects probit model as de-scribed in Wooldridge (2019). This model could estimate a nonlinear model while still allowing for some correlation between the unobserved effect and the explanatory variables (as opposed to the fixed effects model where the relationship between the explanatory variables and the unobserved effect is not specified further).

due to technological age then decrease their technological age by changing occupations. While it would be possible to look at all workers who change their occupation and map where they change from and where they change to, it is not possible to single out the workers who change due to technological age. Together with the fact that technological change is measured per occupation, this makes it difficult to see whether workers decrease their technological age by changing occupations. Since technological change is occupation specific, leaving a higher technologically intensive occupation will almost always result in a decrease in technological age in the data while leaving a less technologically intensive occupation must almost certainly lead to an increase in technological age. Alas, without knowing whether the workers who changed occupations changed due to technological age and then seeing whether those workers decreased their technological age or, even better measuring a truly individual technological age not dependent on the occupation, it is not possible to fully grasp the impact of technological age on workers. It seems clear that in most occupations, especially during the *subsample 79* and *subsample 90*, technological age makes workers more likely to leave their occupations, but we cannot say whether they then decrease their technological age as a result. As before, this is mostly a limitation of the available data and could be fixed by better individual technological change data.

The final point of discussion concerns the way the effect of technological age on wages and on the probability to change occupations is estimated, which can lead to misleading interpretations, especially when comparing the two analyses. The wage analysis employs a log-log model, while the occupation change analysis employs a linear probability model. What this means is that the wage analysis looks at the relative effect of technological age on wages while the occupation change analysis looks at the total effect of technological age on the probability to change occupations. The wage regressions estimate an elasticity, showing the effect of a percent increase in technological age in percent wage terms. This means that in an occupation where overall wage is large, but the total wage effect of technological age is not large, the estimated effect will be smaller still due to the smaller relative change. The opposite is true for an occupation with less wage. The same total impact of technological age would lead to much larger estimated coefficients due to the larger relative impact on the wage. Therefore, the wage analysis does not estimate the total effect of one unit of technological age on one unit of wage but rather the impact of a percent change in technological age on a percentage change in wages. The opposite is true for the occupation change analysis. Here the analysis estimates a total, not a relative effect. The occupation change analysis estimates the impact of a change in a unit of technological age on the probability to leave the occupation. The interpretation for both approaches has to be different and each approach has some positive and some negative implications.

The advantage of the relative approach used in the wage analysis is that in reality the amount of technological change, as well as the wage differs from occupation to occupation. The log-log approach controls for this by showing elasticities. It shows which occupations are more affected by technological age in reality, making it easy to compare the impact of technological age across occupations in the economy. The disadvantage of the log-log approach is that it does not give the impact of one unit of technological age on one unit of wage. While it shows which occupations are more affected by technological age in reality, it does not provide a measurement of how much wage in euro (or dollar) a worker loses due to an increase of technological age by one unit. This limits the comparison between occupations. Even though it is known which occupations get affected more by technological age in relation to the total amount of technological age and wage they have, it is not possible to say which occupation is affected more by a one-unit change in technological age.

The advantages and disadvantages of the occupation change analysis are naturally the opposite of the advantages and disadvantages of the wage analysis. The occupation change analysis makes it possible to tell what the impact of a change in one unit of technological age on the probability to change occupations is. Thus, it makes it possible to compare occupations based on the total impact of technological age, but not in relation to the overall technological change they experience in reality. Some occupations with a large impact of a one-unit increase of technological on the probability to change occupations might not actually experience a lot of technological age and therefore workers are in reality not as strongly affected by technological age as the coefficient would suggest. It would be possible to attempt to gather the impact of technological age in the economy by multiplying the coefficients of the occupation change analysis with the average technological age change per occupation to somewhat control for the different paces of technological change. This changes the impact of technological age on the probability to change occupation dramatically[87], yet shall

[87] This figure can be found in Appendix A16.

not be further part of the analysis as the occupation change analysis does give interesting results worthy of interpretation and a truly relative estimation is impossible due to the absolute effect of leaving an occupation.

Naturally, the different nuances in estimation make it difficult to compare the results of the wage and the occupation change analysis. The wage analysis shows the influence of a percent change in technological age in terms of a percent change in wages while the occupation change analysis shows the impact of a one-unit change in technological age with regards to the probability to leave an occupation. In Section *10*, the impact of technological age on wages is said to be generally negative with the less technologically intensive occupations being hurt the most, while the impact of technological age on the probability to leave occupations is generally positive with less technologically intensive occupations also being hurt the most. With regards to the now discussed nuances in interpretation, the results can be interpreted more precisely. Occupations with less technological change lose relatively more wages due to technological age when compared to occupations with more technological change while a one-unit change in technological age makes workers more likely to leave a less technologically intensive occupation when compared with a one-unit change in technological age in a more technologically intensive occupation. This differing estimation might seem like the analysis comparing two different things, yet the results of the two analyses are valid. It is simply important to keep in mind that there is a percentage change and a unit change impact of technological age being estimated and compared.

In summary, there are several points worthy of discussion regarding the empirical models used in the analysis. For one, the assumption that the influence of technological age on wages and on the probability to change occupations is constant across the sample period might be wrong, which is further credited by the fact the sub sample regressions show differing impacts. Furthermore, the technological age variable might capture more effects than simply the effects of technological age by nature of changing the same amount every year in every occupation. While many control variables are employed in the regression already, the technological age variable could capture some occupation specific yearly shocks. Having a better way to measure technological age on an individual level could remedy this issue. In addition, using a linear probability model can lead to unrealistic coefficients and maybe more research should be done employing other methods, such as the correlated random effects probit approach for example. Finally, it is important to keep in mind that the wage analysis uses a log-log approach to estimate the results of the impact of technological age on wages in terms of elasticities, while the occupation change analysis gives results in terms of a one-unit change in technological age. The differing approaches could lead to difficulties when comparing the results from the two analyses. Overall, these are all issues to keep in mind, most of which are not fatal for the analysis but good possible starting points for further research.

12 Conclusion

This thesis defines the novel concept of technological age and investigates the impact of technological age on workers. Technological change has been a focal point of research in the last years and in most areas, with many influential papers such as Acemoglu (2002), Card and DiNardo (2002) and Autor and Dorn (2013). The way technological change affects workers is generally well understood. Alas, when it comes to the impact technological change has on older workers, the existing research is not very comprehensive. There are studies examining the retirement decisions or computer usage of older workers, such as Ahituv and Zeira (2011) and Bartel and Sicherman (1993). Literature examining the relationship between age and computer usage at work exists, for example Borghans and Ter Weel (2002), de Koning and Gelderblom (2006) and Schleife (2008), as well as literature examining the labor demand of innovative firms with regards to older workers such as Abowd et. al. (2007), Aubert, Caroli and Roger (2006), Beckmann (2007), Behaghel, Caroli, and Roger (2014) and Schleife (2008). However, the specific amount of technological change a person has experienced is not considered in the existing literature. Specifically, the idea that technological change could depreciate human capital and make workers less efficient in their occupations and then using this human capital depreciation as the basis for an empirical analysis is novel. This thesis assumes that younger people are more in touch with new instances of technology while older people generally have a harder time adapting to new developments in technology. The more technological change a person has experienced, the more difficult it is to adapt to new technology. In order to measure this phenomenon more clearly, the thesis first defines the concept of technological age as the person specific amount of technological change a worker has experienced starting with the point of entry into the labor force. The more technological change the worker has experienced, the higher is the technological age and the less efficient is his/her ability to work with new technology. From the idea of technological age as a measure of individual human capital depreciation due to technological change, the thesis develops three hypotheses that it tests:

First hypothesis:

Technological age makes workers less efficient when using new technologies.

Second hypothesis:

Technological age decreases workers' wages.

Third Hypothesis:

Technological age makes workers more likely to change occupations

In order to test the hypotheses, the analysis is split into a wage and an occupation change section, testing Hypothesis 2 and 3 separately while Hypothesis 1 can only be tested indirectly through Hypothesis 2 and 3.

The wage analysis shows that technological age has a negative impact on wages for most occupations in the entire sample, in line with Hypothesis 2. For the other occupations, technological age reveals a positive wage impact across the sample period. While Hypothesis 2 does not hold for all occupations across the sample period of the *overall sample*, the results are robust and significant. The impact of technological age is further specified by the subsample regressions. Those three regressions show that technological age surprisingly had a positive impact on wages in the earlier subsamples, *subsample 79* and *subsample 90,* but had a negative effect on wages across all occupations in *subsample 00*. Thus, Hypothesis 2 cannot be proven for the years 1979-1999 but holds robustly for the years 2000-2006. Furthermore, less technologically intensive occupations are affected more negatively by technological age, both across the *overall sample* and in each of the subsamples. Alas, this analysis cannot give a reason for this phenomenon and further research is necessary.

The occupation change analysis reveals that for most occupations technological age makes workers more likely to leave their occupations, in line with Hypothesis 3, while for some occupations technological age makes workers less likely to leave. The subsample analysis reveals that technological age makes workers more likely to leave their occupations in the earlier years, i.e., in *subsample 79* and *subsample 90,* and makes workers less likely to leave their occupations in the later years of *subsample 00*. As with the wage analysis, the results are robust and significant, only the findings of the *subsample 00* regressions are not robust. Therefore, Hypothesis 3 is robust for the years 1979-1999 but cannot be proven for the years 2000-2006. In addition, a unit increase in technological age generally makes workers in less technologically intensive occupations more likely to leave than workers in highly intensive occupations. Therefore, technological age impacts less technologically intensive workers more, even though the analysis can again not give a reason for this fact and calls for further research.

When combining the two analyses, this thesis makes it clear that technological age indeed has an impact on both, workers' wages and workers' likelihood to leave an occupation. Alas, the analysis cannot confirm Hypothesis 2 and Hypothesis 3 for the entire sample period. However, the analysis shows that the wage and occupation change effect happen at different points in time. First, technological age makes workers more likely to leave their occupation during *subsample 79* and *subsample 90*, showing that Hypothesis 3 can be proven for these years. However, during this phase technological age seems to increase wages for many occupations, potentially lessening the negative impact of technological age on workers overall and making it impossible to prove Hypothesis 2 for many occupations during this time. During *subsample 00*, technological age makes workers less likely to leave their occupations disproving Hypothesis 3 for these years. Yet, technological age leads to a decrease in wages across all occupations during *subsample 00,* proving Hypothesis 2 for this timeframe. Overall, technological age makes workers more likely to leave their occupations in the earlier years and leads to a wage decrease in the later years.

While the way technological age affects workers changes throughout the *overall sample,* technological age still impacts workers across the entire sampled timeframe, however, it simply acts in different ways. Therefore, Hypothesis 1, that technological age makes workers less efficient when using new technologies, cannot be proven for the years 1979-1999. In the earlier years, the measurable impact of technological age on workers is ambiguous. The fact that technological age makes workers in all occupations more likely to leave can show that workers become less efficient when using new technologies. Alas, this possible loss in efficiency is offset by the wage bonus associated with technological age in some occupations in the earlier years. In the later years, Hypothesis 1 can be proven, as there is a negative wage effect associated with technological age in all occupations. The fact that workers are more likely to stay in their occupations due to technological age does not alleviate the negative wage impact. Rather, the fact that workers might be more likely to stay in the occupations where they earn less wages due to technological age does not show that workers do not become less efficient when working with newer technologies. More so, the fact that workers across the board earn less wages due to technological age and they are not more likely to leave their occupations shows that workers across the board are less efficient when using new technologies in line with Hypothesis 1.

The analysis also has some potential areas where more research is needed. Most of the problems stem from the fact that due to data constraints, the technological age measurement is based only on computer usage per occupation. If it was possible to find a better measure for technological age, ideally incorporating changing technology for each individual based on more than simply computer usage, the problem that some technological change happens in the form of something other than computer usage could be solved. Furthermore, in this analysis, some occupations reach a hundred percent computerization before the end of the sample period and therefore technological change and resulting technological age cannot be correctly estimated in these occupations. Estimating technological age on the basis of individual task or individual technology usage would also eliminate the possibility of the technological age variable capturing some occupation specific year fixed effects in the analysis. Generally, finding a better way to estimate technological age might lead to further insights into how technological age affects workers. Additionally, data on training workers is missing from this analysis. It is possible that training could lessen or reverse the impact technological age has on workers. Finally, it is possible that when controlling for training, the impact of technological age on workers could be negative in every occupation. Further research into how training affects technological age and its influence on workers should be a priority in helping to understand the impact of technological age.

In conclusion, technological age is a concept that describes how workers become less efficient when adopting new technologies, the more technological change they have experienced. The influence of technological age on human capital can be neither clearly proven nor disproven for the years 1979-1999. For the years 2000-2006 the concept of technological age can clearly be proven. Furthermore, technological age seems to impact workers employed in less technologically intensive occupations more strongly across the *overall sample* and all subsamples. Especially in this vastly changing technologized world, it is of great importance to understand the impact technological change has on the human capital depreciation of workers. The concept of technological age is a new and precise tool to quantify the influence of technological change on the human capital of workers and give novel insights into the challenges faced in today’s labor markets.

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Appendix

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A1. From the model to the regression

As described in Section *4.1*, the income differences between two individuals at point t, working in the same occupation but coming from two different cohorts τ are given by the personal characteristics δ_{it} and the effect of their starting technology $(A_{j\tau})^{\theta_j}$ [Equation *(6)*]:

$$\frac{I^i_{\tau jt}}{I^k_{\tau' jt}} = \frac{\delta_{it}}{\delta_{kt}} \frac{(A_{j\tau})^{\theta_j}}{(A_{j\tau'})^{\theta_j}} \tag{6}$$

Since both individual's income is taken at point t, $\mathrm{A_{j\tau}}$ implicitly also encapsulates the difference between A_{jt} and $\mathrm{A_{j\tau}}$, as A_{jt} is the same for both individuals. Because this thesis is interested in the occupational effect of technological age, θ_j is the variable of interest and must be estimated.

$$ln\, I^i_{\tau jt} = \theta_j \ln\big(A_{j\tau}\big) + ln\, \delta_{ijt} \tag{9}$$

Equation *(9)* almost describes the regression function already. Alas, since technology takes on the value zero, taking logs is impossible. As described in Section *4.2*, to circumvent this issue one is added to all technology values. The resulting regression function is only slightly expanded upon to arrive at the used regression function.

$$ln\, I^i_{\tau jt} = \beta_0 + \theta_j \ln\big(1 + A_{j\tau}\big) + \beta_1 ln\, \delta_{ijt} \tag{10}$$

Mainly, due to the panel nature of the data, using a person fixed effects model allows for taking into account the panel structure without having to adhere to the random effects assumptions[88]. Alas, the fixed effects estimator only takes within variation into account, which is why the starting technological level per occupation does not yield results. Rather the change in technological age must be regressed on the change in

[88] namely that the unobserved effects are uncorrelated with the explanatory variables.

income in order to lead to an estimation of θ_j. Finally, expanding on the personal characteristics δ_{ijt} with time fixed effects, state and industry dummies will only improve the accuracy of the estimation, leading to the regression function:

$$(7) \quad lnI_{ij\tau t} = \beta_0 + \theta_j\{[ln(1 + A_{jt}) - ln(1 + A_{j\tau})] * occupation_{ijt}\} + \beta_1 \ln \delta_{it} + \beta_2 vocTrain_{it} + \beta_{3j} occupation_{ijt} + \beta_4 state_{it} + \beta_5 Ind_{it} + \beta_{6t} * d_{it} + \varepsilon_{ij\tau t}$$

A2. *KldB88* original sections

Table A1 shows the *KldB88* sections used in the *SIAB Data* and consequently in this thesis. Furthermore, *Table A1* shows which sections from the unchanged *KldB88* classification were merged together and which sections were dropped in the *SIAB Data*.

Table A1: *KldB88 section and variable names as used in SIAB Data and in the original KldB88 sections*

Number	Section in Thesis (in accordance with *SIAB Data*)	Original sections (in accordance with *KldB88*)
1	Farmers, Animal Breeding, Fishing	Pflanzenbauer, Tierzüchter, Fischeriberufe
2	Miners, Mineral Exploitation, Stone Workers, Building Material Production	Bergleute, Mineralgewinner
		Steinbearbeiter, Baustoffhersteller (merged into number 2)
3	Ceramic, Glas Production	Keramiker, Glasmacher
4	Chemistry Workers, Synthetics Production	Chemiearbeiter, Kunststoffverarbeiter
5	Paper making and processing, Printing	Papierhersteller, -verarbeiter, Drucker
6	Wood Treating, Wooden Goods Production and Similar	Holzaufbereiter, Holzwarenfertiger und verwandte Berufe
7	Metal Making and Working	Metallerzeuger, -bearbeiter
8	Locksmith, Mechanics and Similar	Schlosser, Mechaniker und zugeordnete Berufe
9	Electricians	Elektriker
10	Assembly and Other Metal Works	Montierer und Metallberufe, a.n.g.
11	Textile and Clothing Occupations, Leather Production and Leather and Fur Processing	Textil- und Bekleidungsberufe
		Lederhersteller, Leder- und Fellverarbeiter (merged into number 11)
12	Food Occupations	Ernährungsberufe
13	Construction	Bauberufe
14	Interior Construction, Upholsterer	Bau-, Raumausstatter, Polsterer
15	Carpenter, Model Maker	Tischler, Modellbauer
16	Painter, Varnisher and similar Occupations	Maler, Lackierer und verwandte Berufe
17	Product Tester, Shipment Preparation	Warenprüfer, Versandfertigmacher
		Hilfsarbeiter ohne nähere Tätigkeitsangabe (not part of the *SIAB Data*)
18	Machinist and similar Occupations	Maschinisten und zugehörige Berufe
19	Engineers, Chemists, Physicists, Mathmaticians	Ingenieure, Chemiker, Physiker, Mathematiker
20	Technicians, Technical Specialists	Techniker, Technische Sonderfachkräfte
21	Goods Merchants	Warenkaufleute

Number	Section in Thesis (in accordance with ***SIAB Data***)	Original sections (in accordance with ***KldB88***)
22	Service Merchants and similar Occupations	Dienstleistungskaufleute und zugehörige Berufe
23	Traffic Occupations	Verkehrsberufe
24	Organization, Administration and Office Occupations	Organisations-, Verwaltungs-, Büroberufe
25	Regulatory and Safety Occupations	Ordnungs-, Sicherheitsberufe
26	Writers, Artists	Schriftwerkschaffende, schriftwerkverkordnende sowie künstlerische Berufe
27	Healthcare Occupations	Gesundheitsdienstberufe
28	Social and Educational Occupations, other not mentioned Social Science and Science Occupations	Sozial- und Erziehungsberufe, anderweitig nicht genannte geistes- und naturwissenschaftliche Berufe
		Allgemeine Dienstleistungsberufe (not part of the SIAB Data)
		Sonstige Arbeitskräfte (not part of the SIAB Data)

Note: Red original KldB88 sections are either merged into another section or not part of the SIAB sections.

A3. *KldB2010* sections

Due to the differing nature of the two occupation classifications in order to better depict the changing occupations through time, *KldB2010* includes a more modern focus of occupation classification, while *KldB88* is more so focused on the craft and manufacturing occupations[89]. Of course, this means that not every *KldB88* occupation can be assigned to a corresponding *KldB2010* occupation. All waves up to wave 2006 of the *BIBB Data* are constructed using *KldB88* and the lack of attrition when simply using the older *KldB88* was thought to be more important than using the newer *KldB2010* format. *Table A2* shows the *KldB2010* occupations while the transposition can be done according to the "Umsteigeschlüssel von der Klassifizierung der Berufe 1988 (4-Steller) zur Klassifikation der Berufe 2010 (5-Steller)" by the Bundesagentur für Arbeit. (2011).

Table A2: *KldB2010 section names by number*

Number	KldB2010 Section
11	agriculture, forestry, and farming
12	gardening and floristry
21	production and processing of raw materials, glass- and ceramic-making and -processing
22	plastic-making and -processing, and wood-working and -processing
23	paper-making and -processing, printing, and in technical media design
24	metal-making and -working, and in metal construction
25	machine-building and automotive industry
26	mechatronics, energy electronics and electrical engineering
27	technical research and development, construction, and production planning and scheduling
28	textile- and leather-making and -processing
29	food-production and -processing
31	construction scheduling, architecture and surveying
32	building construction above and below ground
33	interior construction
34	building services engineering and technical building services
41	mathematics, biology, chemistry and physics
42	geology, geography and environmental protection
43	computer science, information and communication technology

[89] Matthes and Paulus (2013) give a detailed account on the difference between *KldB88* and *KldB2010* and why the *KldB88* had to be updated.

Number	KldB2010 Section
51	traffic and logistics (without vehicle driving)
52	Drivers and operators of vehicles and transport equipment
53	safety and health protection, security and surveillance
54	cleaning services
61	purchasing, sales and trading
62	Sales occupations in retail trade
63	tourism, hotels and restaurants
71	business management and organisation
72	financial services, accounting and tax consultancy
73	law and public administration
81	Medical and health care occupations
82	non-medical healthcare, body care, wellness and medical technicians
83	education and social work, housekeeping, and theology
84	teaching and training
91	philology, literature, humanities, social sciences, and economics
92	advertising and marketing, in commercial and editorial media design
93	product design, artisan craftwork, fine arts and the making of musical instruments
94	performing arts and entertainment

Note: The sections numbers are the original KLdB2010 section numbers and are hence not continuous.

A4. Technological progression according to *BIBB Data* – full tables

Table A3: *Share of computer users per occupation per year, 1979-1985*

KldB88	Wave						
	1979	1980	1981	1982	1983	1984	1985
agriculture_fishing (1)	0.0036	0.0061	0.0086	0.0110	0.0135	0.0160	0.0184
miners_stone_workers (2)	0.0173	0.0174	0.0175	0.0176	0.0176	0.0177	0.0178
ceramic_glas (3)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0
chemistry_synthetic_workers (4)	0.0230	0.0334	0.0437	0.0541	0.0644	0.0748	0.0851
paper_print (5)	0.0675	0.0765	0.0856	0.0947	0.1037	0.1128	0.1219
woodworking (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0
metal_works (7)	0.0019	0.0046	0.0073	0.0099	0.0126	0.0153	0.018
mechanics (8)	0.0082	0.0124	0.0165	0.0207	0.0248	0.0290	0.0331
electricians (9)	0.0451	0.0547	0.0644	0.0740	0.0837	0.0933	0.103
assembly (10)	0.0046	0.0114	0.0181	0.0248	0.0315	0.0383	0.045
textile_clothing_leather_fur (11)	0.0035	0.0052	0.0070	0.0087	0.0105	0.0122	0.0139
food (12)	0.0032	0.0043	0.0054	0.0065	0.0076	0.0087	0.0098
construction (13)	0.0000	0.0012	0.0024	0.0036	0.0047	0.0059	0.0071
interior_construction (14)	0.0000	0.0019	0.0037	0.0056	0.0075	0.0094	0.0112
carpenter (15)	0.0000	0.0018	0.0036	0.0054	0.0073	0.0091	0.0109
painter (16)	0.0000	0.0015	0.0030	0.0045	0.0060	0.0074	0.0089
product_testing (17)	0.0112	0.0183	0.0253	0.0324	0.0394	0.0465	0.0535
machinist (18)	0.0114	0.0185	0.0257	0.0328	0.0399	0.0470	0.0541
engineer_math_chem (19)	0.1565	0.2024	0.2482	0.2941	0.3400	0.3859	0.4318
technical_specilaist (20)	0.0980	0.1289	0.1599	0.1908	0.2217	0.2526	0.2835
goods_merchants (21)	0.0300	0.0455	0.0610	0.0765	0.0921	0.1076	0.1231
service_merchants (22)	0.1942	0.2420	0.2898	0.3376	0.3854	0.4332	0.4809
traffic (23)	0.0230	0.0271	0.0313	0.0354	0.0395	0.0436	0.0478
administration (24)	0.1179	0.1581	0.1983	0.2384	0.2786	0.3188	0.3589
regulatory_safety (25)	0.0607	0.0759	0.0911	0.1062	0.1214	0.1366	0.1517
writing_art (26)	0.0311	0.0556	0.0801	0.1046	0.1291	0.1536	0.178
healthcare (27)	0.0362	0.0447	0.0532	0.0618	0.0703	0.0788	0.0874
social_education_science (28)	0.0311	0.0426	0.0541	0.0656	0.0771	0.0885	0.1

Note: The waves providing the computer use data are marked by “wave”. Computer use progression between the waves is assumed to be linear.

Table A4: *Share of computer users per occupation per year, 1986-1991*

KldB88	Wave 1986	1987	1988	1989	1990	1991
agriculture_fishing (1)	0.0209	0.0270	0.0330	0.0391	0.0452	0.0513
miners_stone_workers (2)	0.0179	0.0247	0.0315	0.0383	0.0452	0.0520
ceramic_glas (3)	0.0000	0.0063	0.0125	0.0188	0.0250	0.0313
chemistry_synthetic_workers (4)	0.0955	0.1085	0.1216	0.1346	0.1477	0.1607
paper_print (5)	0.1310	0.1560	0.1810	0.2060	0.2310	0.2560
woodworking (6)	0.0000	0.0045	0.0090	0.0135	0.0180	0.0225
metal_works (7)	0.0206	0.0310	0.0414	0.0517	0.0621	0.0725
mechanics (8)	0.0373	0.0500	0.0626	0.0753	0.0880	0.1007
electricians (9)	0.1127	0.1398	0.1669	0.1941	0.2212	0.2483
assembly (10)	0.0517	0.0532	0.0546	0.0561	0.0576	0.0590
textile_clothing_leather_fur (11)	0.0157	0.0173	0.0189	0.0205	0.0221	0.0237
food (12)	0.0109	0.0149	0.0190	0.0230	0.0270	0.0310
construction (13)	0.0083	0.0110	0.0138	0.0165	0.0192	0.0219
interior_construction (14)	0.0131	0.0205	0.0278	0.0352	0.0425	0.0499
carpenter (15)	0.0127	0.0237	0.0347	0.0457	0.0567	0.0677
painter (16)	0.0104	0.0168	0.0231	0.0295	0.0358	0.0422
product_testing (17)	0.0606	0.0811	0.1016	0.1222	0.1427	0.1632
machinist (18)	0.0612	0.0656	0.0700	0.0744	0.0787	0.0831
engineer_math_chem (19)	0.4776	0.5153	0.5529	0.5906	0.6282	0.6659
technical_specilaist (20)	0.3144	0.3446	0.3747	0.4049	0.4350	0.4652
goods_merchants (21)	0.1386	0.1533	0.1681	0.1828	0.1976	0.2123
service_merchants (22)	0.5287	0.5688	0.6089	0.6490	0.6891	0.7291
traffic (23)	0.0519	0.0607	0.0696	0.0785	0.0873	0.0962
administration (24)	0.3991	0.4367	0.4743	0.5119	0.5495	0.5870
regulatory_safety (25)	0.1669	0.1928	0.2187	0.2446	0.2705	0.2963
writing_art (26)	0.2025	0.2375	0.2724	0.3074	0.3424	0.3773
healthcare (27)	0.0959	0.1235	0.1510	0.1786	0.2062	0.2338
social_education_science (28)	0.1115	0.1357	0.1599	0.1841	0.2083	0.2325

Note: The waves providing the computer use data are marked by "wave". Computer use progression between the waves is assumed to be linear.

Table A5: *Share of computer users per occupation per year, 1992-1998*

KldB88	Wave 1992	1993	1994	1995	1996	1997	1998
agriculture_fishing (1)	0.0574	0.0710	0.0847	0.0984	0.1120	0.1257	0.1393
miners_stone_workers (2)	0.0588	0.0602	0.0615	0.0628	0.0642	0.0655	0.0668
ceramic_glas (3)	0.0375	0.0607	0.0839	0.1071	0.1304	0.1536	0.1768
chemistry_synthetic_workers (4)	0.1738	0.1966	0.2194	0.2421	0.2649	0.2877	0.3105
paper_print (5)	0.2810	0.2939	0.3067	0.3196	0.3324	0.3453	0.3582
woodworking (6)	0.0270	0.0232	0.0193	0.0154	0.0116	0.0077	0.0039
metal_works (7)	0.0828	0.0868	0.0907	0.0946	0.0985	0.1024	0.1063
mechanics (8)	0.1133	0.1304	0.1475	0.1646	0.1817	0.1988	0.2159
electricians (9)	0.2755	0.2997	0.3239	0.3481	0.3723	0.3964	0.4206
assembly (10)	0.0605	0.0700	0.0796	0.0892	0.0987	0.1083	0.1178
textile_clothing_leather_fur (11)	0.0253	0.0312	0.0371	0.0430	0.0489	0.0548	0.0608
food (12)	0.0351	0.0429	0.0508	0.0586	0.0665	0.0743	0.0822
construction (13)	0.0246	0.0289	0.0332	0.0374	0.0417	0.0460	0.0502
interior_construction (14)	0.0573	0.0658	0.0744	0.0830	0.0916	0.1001	0.1087
carpenter (15)	0.0787	0.0915	0.1042	0.1170	0.1298	0.1425	0.1553
painter (16)	0.0485	0.0530	0.0574	0.0618	0.0663	0.0707	0.0751
product_testing (17)	0.1837	0.1956	0.2074	0.2193	0.2311	0.2430	0.2548
machinist (18)	0.0875	0.0999	0.1123	0.1246	0.1370	0.1494	0.1618
engineer_math_chem (19)	0.7035	0.7347	0.7658	0.7970	0.8281	0.8593	0.8905
technical_specilaist (20)	0.4953	0.5356	0.5759	0.6162	0.6565	0.6968	0.7371
goods_merchants (21)	0.2271	0.2551	0.2831	0.3111	0.3392	0.3672	0.3952
service_merchants (22)	0.7692	0.7930	0.8169	0.8407	0.8645	0.8883	0.9121
traffic (23)	0.1051	0.1163	0.1276	0.1389	0.1502	0.1614	0.1727
administration (24)	0.6246	0.6621	0.6995	0.7370	0.7745	0.8119	0.8494
regulatory_safety (25)	0.3222	0.3616	0.4009	0.4402	0.4796	0.5189	0.5582
writing_art (26)	0.4123	0.4476	0.4830	0.5184	0.5538	0.5892	0.6246
healthcare (27)	0.2613	0.3100	0.3587	0.4074	0.4561	0.5048	0.5535
social_education_science (28)	0.2567	0.2943	0.3318	0.3694	0.4069	0.4445	0.4821

Note: The waves providing the computer use data are marked by "wave". Computer use progression between the waves is assumed to be linear.

Table A6: *Share of computer users per occupation per year, 1999-2006*

KldB88	Wave 1999	2000	2001	2002	2003	2004	2005	Wave 2006
agriculture_fishing (1)	0.1530	0.2119	0.2708	0.3298	0.3887	0.4476	0.5065	0.5655
miners_stone_workers (2)	0.0682	0.1317	0.1952	0.2587	0.3223	0.3858	0.4493	0.5128
ceramic_glas (3)	0.2000	0.2407	0.2814	0.3221	0.3628	0.4035	0.4442	0.4848
chemistry_synthetic_workers (4)	0.3333	0.3988	0.4642	0.5296	0.5951	0.6605	0.7259	0.7914
paper_print (5)	0.3710	0.4298	0.4885	0.5473	0.6061	0.6648	0.7236	0.7823
woodworking (6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
metal_works (7)	0.1102	0.1974	0.2846	0.3717	0.4589	0.5461	0.6333	0.7204
mechanics (8)	0.2330	0.3039	0.3748	0.4457	0.5166	0.5875	0.6584	0.7293
electricians (9)	0.4448	0.5008	0.5567	0.6126	0.6685	0.7244	0.7803	0.8362
assembly (10)	0.1274	0.1954	0.2635	0.3316	0.3996	0.4677	0.5357	0.6038
textile_clothing_leather_fur (11)	0.0667	0.1190	0.1713	0.2236	0.2759	0.3282	0.3805	0.4328
food (12)	0.0901	0.1309	0.1718	0.2127	0.2535	0.2944	0.3353	0.3761
construction (13)	0.0545	0.0868	0.1190	0.1513	0.1835	0.2158	0.2480	0.2803
interior_construction (14)	0.1173	0.1739	0.2306	0.2873	0.3440	0.4007	0.4573	0.5140
carpenter (15)	0.1681	0.2260	0.2839	0.3419	0.3998	0.4577	0.5156	0.5735
painter (16)	0.0796	0.1375	0.1955	0.2534	0.3113	0.3693	0.4272	0.4851
product_testing (17)	0.2667	0.3289	0.3911	0.4533	0.5155	0.5777	0.6399	0.7021
machinist (18)	0.1741	0.2539	0.3336	0.4133	0.4930	0.5727	0.6524	0.7321
engineer_math_chem (19)	0.9216	0.9317	0.9418	0.9520	0.9621	0.9722	0.9823	0.9925
technical_specilaist (20)	0.7774	0.8050	0.8326	0.8602	0.8877	0.9153	0.9429	0.9705
goods_merchants (21)	0.4232	0.4713	0.5193	0.5674	0.6154	0.6635	0.7115	0.7596
service_merchants (22)	0.9359	0.9434	0.9510	0.9585	0.9660	0.9735	0.9811	0.9886
traffic (23)	0.1840	0.2391	0.2943	0.3495	0.4047	0.4599	0.5151	0.5702
administration (24)	0.8869	0.9008	0.9147	0.9286	0.9426	0.9565	0.9704	0.9843
regulatory_safety (25)	0.5975	0.6364	0.6752	0.7140	0.7528	0.7917	0.8305	0.8693
writing_art (26)	0.6599	0.6963	0.7327	0.7691	0.8054	0.8418	0.8782	0.9145
healthcare (27)	0.6022	0.6443	0.6864	0.7285	0.7705	0.8126	0.8547	0.8968
social_education_science (28)	0.5196	0.5695	0.6193	0.6691	0.7190	0.7688	0.8187	0.8685

Note: The waves providing the computer use data are marked by "wave". Computer use progression between the waves is assumed to be linear.

A5. BIBB Data with *KldB2010*

A5.i. Data Description *BIBB Data* extension when using *KldB2010*

As mentioned in Section *5.1.2*, the *BIBB Data* includes a sixth wave that does not include *KldB88* occupation classifications, which is used for some robustness checks. *Table 1: BiBB Data waves, years, individuals interviewed and included number of variables,* gives the years, individuals interviewed and included number of variables per wave. Furthermore, all waves but wave 6 had the *KldB88* transposed by me using the the “Umsteigeschlüssel von der Klassifizierung der Berufe 1988 (4-Steller) zur Klassifikation der Berufe 2010 (5-Steller)“ by the Bundesagentur für Arbeit. (2011).

Extra question of wave 6:

2012, (Wave 6): For wave 6, the question is almost similar to wave 5; “Please think of your occupational activity as I will now give you a number of specific job tasks. Please tell me how often these job tasks occur in your work, whether they occur often, sometimes or never.” Question F318 asks working with computers. As before, if a person answered sometimes or often, he/she is counted as using a computer.

A5.ii. Descriptive statistics BIBB Data using *KldB2010*

Table A7: *Number of observations per KldB2010 and percentage of observations per KldB88 as part of total observations, wave 1979, 1986 and 1992*

		1979		1986		1992	
KldB2010	Number	Freq.	Percent	Freq.	Percent	Freq.	Percent
agriculture	11	634	2.31	623	2.45	1,179	3.46
gardening	12	193	0.7	242	0.95	310	0.91
raw_material_prod	21	250	0.91	174	0.68	248	0.73
plastic_wood_process	22	407	1.48	454	1.78	531	1.56
paper_process	23	347	1.26	371	1.46	354	1.04
metal_making	24	1,887	6.86	1,573	6.18	1,612	4.74
machine_car_build	25	1,590	5.78	1,464	5.76	1,992	5.85
electrical_engineer	26	455	1.65	501	1.97	1,380	4.06
tech_research_construction	27	1,286	4.68	779	3.06	1,141	3.35
textile_process	28	793	2.88	666	2.62	523	1.54
food_process	29	426	1.55	354	1.39	779	2.29
architecture	31	285	1.04	328	1.29	415	1.22
construction	32	645	2.35	608	2.39	1,069	3.14
interior_constr	33	506	1.84	476	1.87	631	1.85
build_engineer	34	370	1.35	369	1.45	679	2
math_bio_chem	41	378	1.37	388	1.53	498	1.46
geo	42	21	0.08	27	0.11	80	0.24
IT	43	130	0.47	263	1.03	358	1.05
logistics	51	1,075	3.91	976	3.84	1,450	4.26
drivers	52	1,017	3.7	852	3.35	1,285	3.78
safety	53	731	2.66	544	2.14	680	2
cleaning_service	54	468	1.7	502	1.97	797	2.34
purchasing_sales	61	1,310	4.76	1,180	4.64	844	2.48
retail	62	1,418	5.16	1,359	5.34	2,341	6.88
tourism	63	328	1.19	525	2.06	540	1.59
management	71	5,212	18.95	3,928	15.44	3,528	10.37
finance	72	1,243	4.52	1,238	4.87	1,590	4.67
law	73	579	2.11	577	2.27	2,096	6.16
medical	81	1,078	3.92	1,147	4.51	1,489	4.38
wellness	82	371	1.35	396	1.56	608	1.79
education	83	596	2.17	738	2.9	956	2.81
teaching	84	1,026	3.73	1,170	4.6	1,510	4.44
social_science	91	113	0.41	200	0.79	102	0.3
marketing	92	150	0.55	207	0.81	148	0.43
craftwork	93	145	0.53	160	0.63	154	0.45
entertainment	94	37	0.13	76	0.3	132	0.39
Total		27,500	100	25,435	100	34,029	100

Table A8: *Number of observations per KldB88 and percentage of observations per KldB88 as part of total observations, wave 1999, 2006 and 2012*

		1999		2006		2012	
KldB2010	Number	Freq.	Percent	Freq.	Percent	Freq.	Percent
agriculture	11	530	1.56	218	1.09	188	0.95
gardening	12	425	1.25	170	0.85	159	0.8
raw_material_prod	21	245	0.72	110	0.55	53	0.27
plastic_wood_process	22	488	1.43	235	1.18	212	1.07
paper_process	23	334	0.98	210	1.05	202	1.02
metal_making	24	1,062	3.12	647	3.25	556	2.8
machine_car_build	25	1,614	4.74	1,025	5.15	890	4.49
electrical_engineer	26	1,119	3.29	689	3.46	723	3.65
tech_research_construction	27	1,011	2.97	430	2.16	502	2.53
textile_process	28	310	0.91	90	0.45	97	0.49
food_process	29	751	2.21	336	1.69	371	1.87
architecture	31	360	1.06	223	1.12	240	1.21
construction	32	946	2.78	221	1.11	196	0.99
interior_constr	33	604	1.78	204	1.02	180	0.91
build_engineer	34	859	2.53	433	2.17	347	1.75
math_bio_chem	41	384	1.13	285	1.43	280	1.41
geo	42	91	0.27	59	0.3	51	0.26
IT	43	475	1.4	636	3.19	589	2.97
logistics	51	1,429	4.2	865	4.34	813	4.1
drivers	52	1,095	3.22	517	2.6	517	2.61
safety	53	642	1.89	401	2.01	343	1.73
cleaning_service	54	736	2.16	314	1.58	350	1.77
purchasing_sales	61	923	2.71	672	3.37	631	3.18
retail	62	2,706	7.95	1,121	5.63	1,211	6.11
tourism	63	753	2.21	332	1.67	380	1.92
management	71	4,027	11.84	2,218	11.14	1,941	9.79
finance	72	1,608	4.73	1,278	6.42	1,303	6.57
law	73	1,830	5.38	1,232	6.19	1,370	6.91
medical	81	2,032	5.97	1,506	7.56	1,593	8.04
wellness	82	805	2.37	398	2	535	2.7
education	83	1,330	3.91	863	4.33	1,004	5.07
teaching	84	1,631	4.79	1,295	6.5	1,202	6.06
social_science	91	79	0.23	63	0.32	60	0.3
marketing	92	339	1	349	1.75	486	2.45
craftwork	93	165	0.49	81	0.41	64	0.32
entertainment	94	157	0.46	100	0.5	112	0.57
Total		34,019	100	19,913	100	19,822	100

Table A9: *Number of observations per KldB201, who do and who do not use a computer, waves 1979, 1986 and 1992*

		1979		1986		1992	
		Computer usage		Computer usage		Computer usage	
KldB2010	Number	No	Yes	No	Yes	No	Yes
agriculture	11	631	3	611	12	1,071	108
gardening	12	193	0	236	6	295	15
raw_material_prod	21	247	3	172	2	227	21
plastic_wood_process	22	407	0	446	8	477	54
paper_process	23	329	18	329	42	243	111
metal_making	24	1,878	9	1,526	47	1,447	165
machine_car_build	25	1,530	60	1,305	159	1,620	372
electrical_engineer	26	394	61	335	166	858	522
tech_research_construction	27	1,182	104	545	234	512	629
textile_process	28	791	2	658	8	504	19
food_process	29	424	2	349	5	747	32
architecture	31	247	38	218	110	173	242
construction	32	645	0	601	7	1,029	40
interior_constr	33	506	0	473	3	600	31
build_engineer	34	369	1	356	13	620	59
math_bio_chem	41	341	37	277	111	281	217
geo	42	21	0	25	2	39	41
IT	43	17	113	22	241	20	338
logistics	51	1,041	34	869	107	1,168	282
drivers	52	1,008	9	834	18	1,233	52
safety	53	683	48	434	110	427	253
cleaning_service	54	468	0	500	2	792	5
purchasing_sales	61	1,249	61	916	264	438	406
retail	62	1,393	25	1,273	86	2,008	333
tourism	63	317	11	486	39	455	85
management	71	4,748	464	2,581	1,347	1,318	2,210
finance	72	972	271	472	766	333	1,257
law	73	514	65	410	167	919	1,177
medical	81	1,039	39	1,037	110	1,101	388
wellness	82	370	1	387	9	569	39
education	83	594	2	723	15	886	70
teaching	84	984	42	1,044	126	1,058	452
social_science	91	82	31	128	72	37	65
marketing	92	139	11	130	77	41	107
craftwork	93	145	0	152	8	139	15
entertainment	94	34	3	69	7	104	28
Total		25,932	1,568	20,929	4,506	23,789	10,240

Table A10: *Number of observations per KldB2010, who do and who do not use a computer, wave 1999, 2006 and 2012*

		1999		2006		2012	
		Computer usage		Computer usage		Computer usage	
KldB2010	Number	No	Yes	No	Yes	No	Yes
agriculture	11	452	78	80	138	45	143
gardening	12	381	44	92	78	90	69
raw_material_prod	21	216	29	52	58	15	38
plastic_wood_process	22	407	81	80	155	73	139
paper_process	23	182	152	34	176	21	181
metal_making	24	885	177	181	466	139	417
machine_car_build	25	1,082	532	144	881	135	755
electrical_engineer	26	510	609	68	621	65	658
tech_research_construction	27	201	810	25	405	14	488
textile_process	28	278	32	47	43	37	60
food_process	29	678	73	205	131	162	209
architecture	31	44	316	1	222	6	234
construction	32	906	40	161	60	116	80
interior_constr	33	545	59	121	83	99	81
build_engineer	34	714	145	179	254	130	217
math_bio_chem	41	123	261	13	272	18	262
geo	42	15	76	2	57	2	49
IT	43	18	457	0	636	0	589
logistics	51	901	528	247	618	222	591
drivers	52	1,019	76	329	188	291	226
safety	53	221	421	32	369	26	317
cleaning_service	54	725	11	282	32	295	55
purchasing_sales	61	209	714	21	651	14	617
retail	62	1,868	838	375	746	354	857
tourism	63	508	245	136	196	120	260
management	71	451	3,576	35	2,183	22	1,919
finance	72	35	1,573	4	1,274	2	1,301
law	73	175	1,655	7	1,225	11	1,359
medical	81	812	1,220	155	1,351	107	1,486
wellness	82	629	176	186	212	171	364
education	83	931	399	236	627	204	800
teaching	84	565	1,066	49	1,246	29	1,173
social_science	91	6	73	1	62	1	59
marketing	92	36	303	3	346	2	484
craftwork	93	108	57	19	62	10	54
entertainment	94	101	56	28	72	14	98
Total		16,962	17,057	3,635	16,278	3,066	16,756

A5.iii. Technological progression according do *BIBB Data* using *KldB2010*

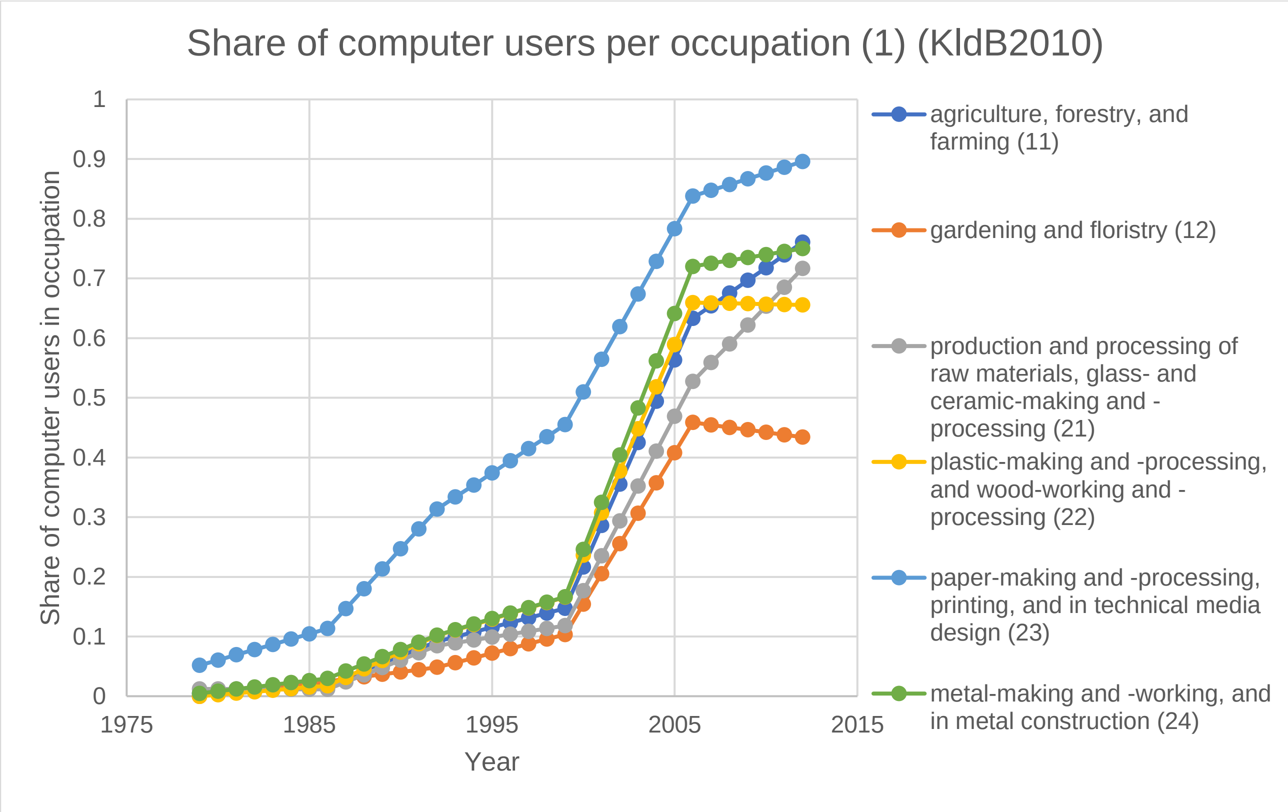

Figure A1: *Share of computer users per occupation (1) (KldB2010)*

Note: Yearly share of computer users for KldB2010 11-24, based on Table A11 to Table A15 in Appendix A5.iv.

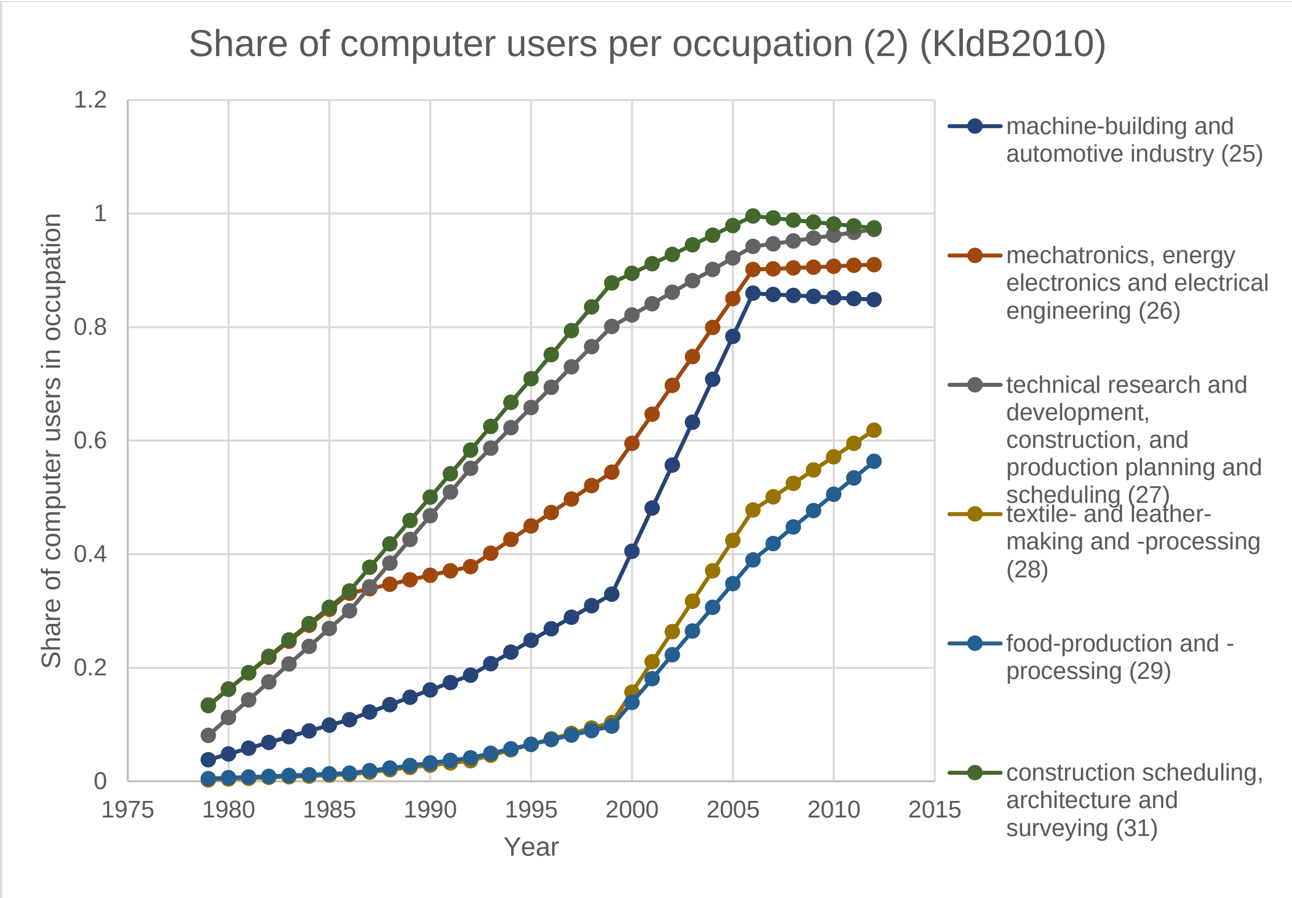

Figure A2: *Share of computer users per occupation (2) (KldB2010)*

Note: Yearly share of computer users for KldB2010 25-31, based on Table A11 to Table A15 in Appendix A5.iv.

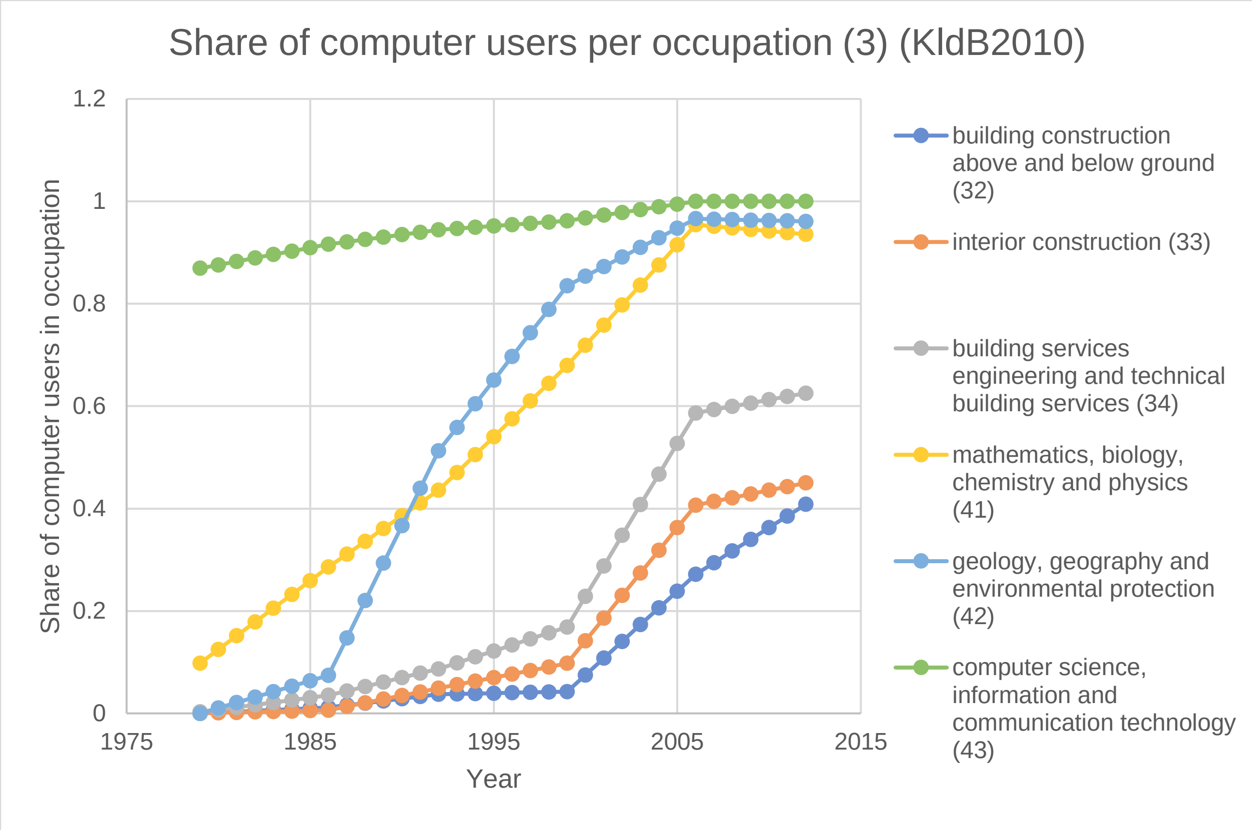

Figure A3: *Share of computer users per occupation (3) (KldB2010)*

Note: Yearly share of computer users for KldB2010 32-43, based on based on Table A11 to Table A15 in Appendix A5.iv.

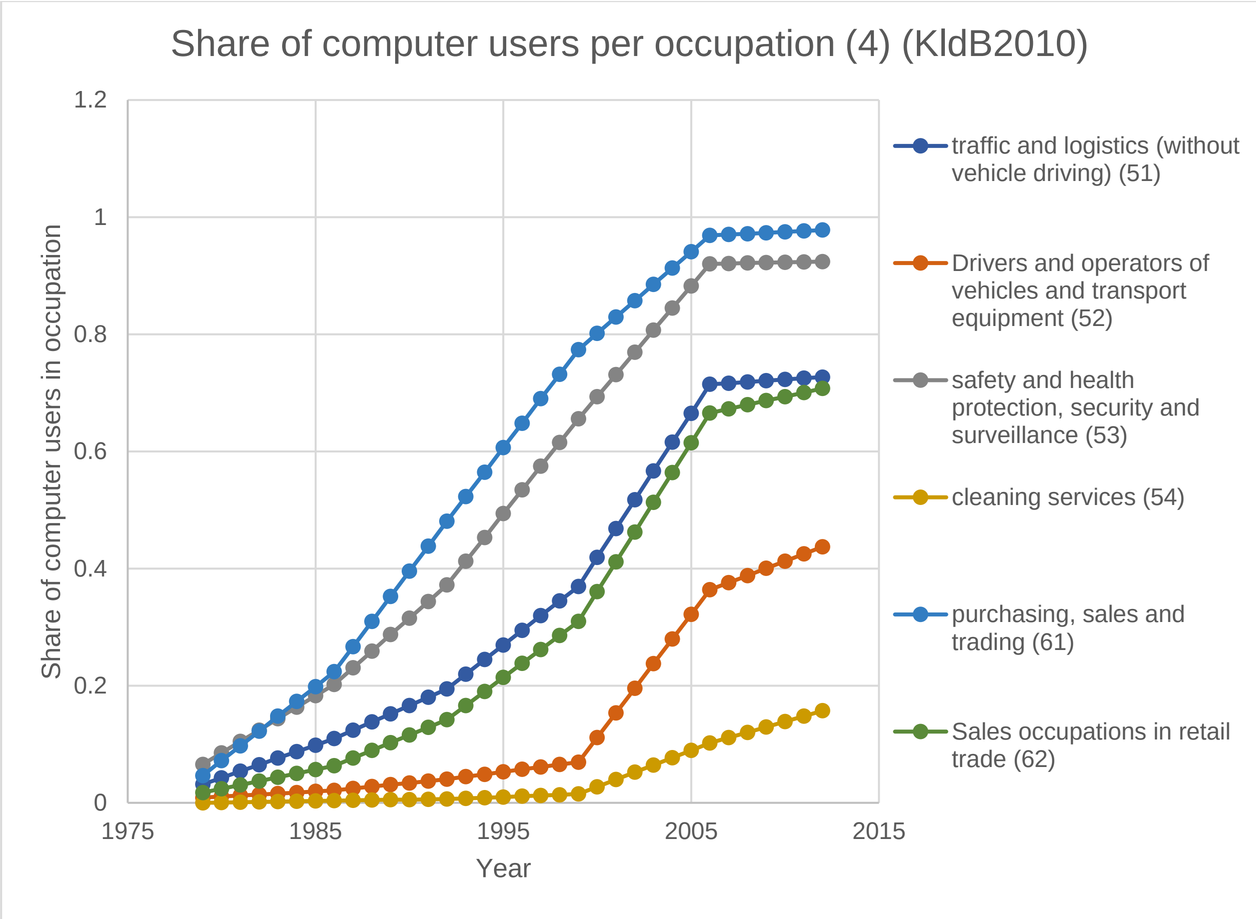

Figure A4: *Share of computer users per occupation (4) (KldB2010)*

Note: Yearly share of computer users for KldB2010 51-62, based on based on Table A11 to Table A15 in Appendix A5.iv.

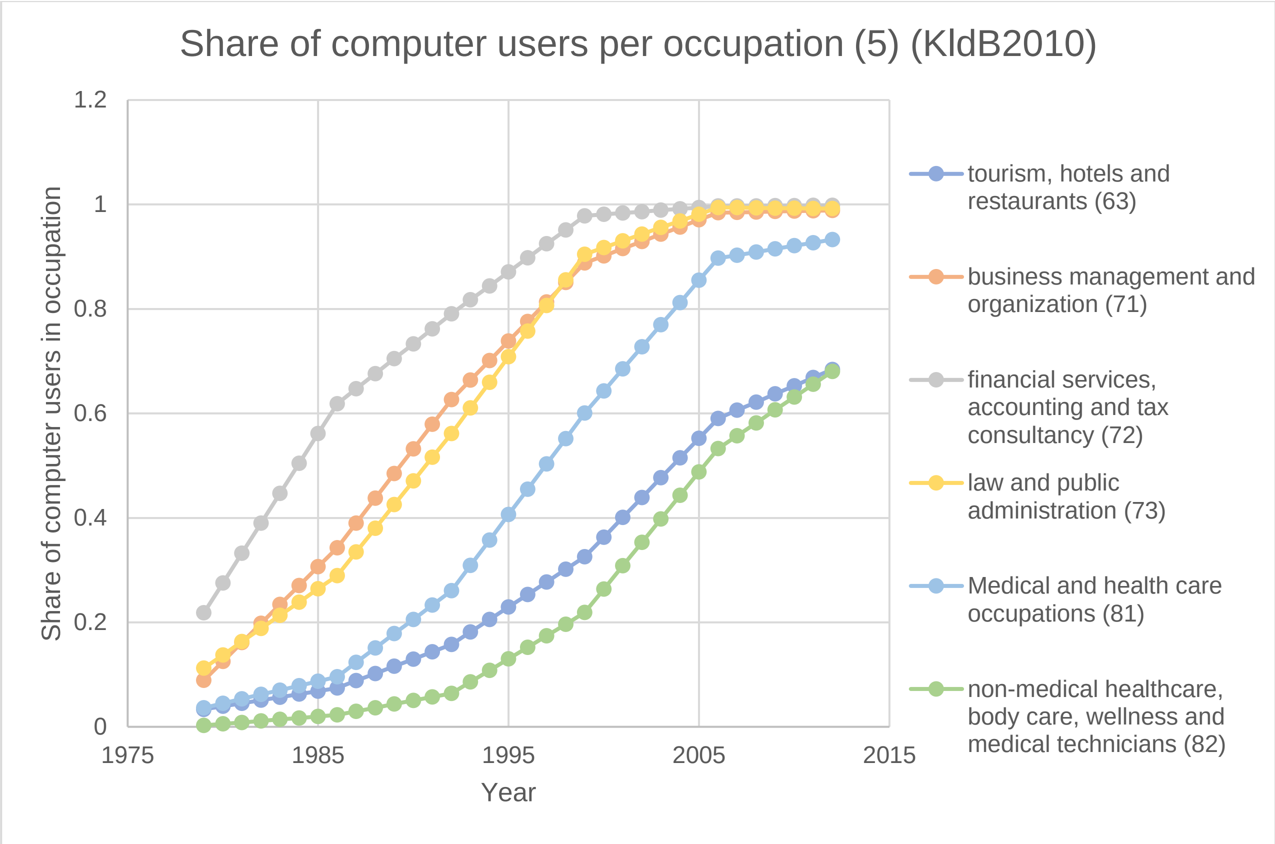

Figure A5: *Share of computer users per occupation (5) (KldB2010)*

Note: Yearly share of computer users for KldB2010 63-82, based on based on Table A11 to Table A15 in Appendix A5.iv.

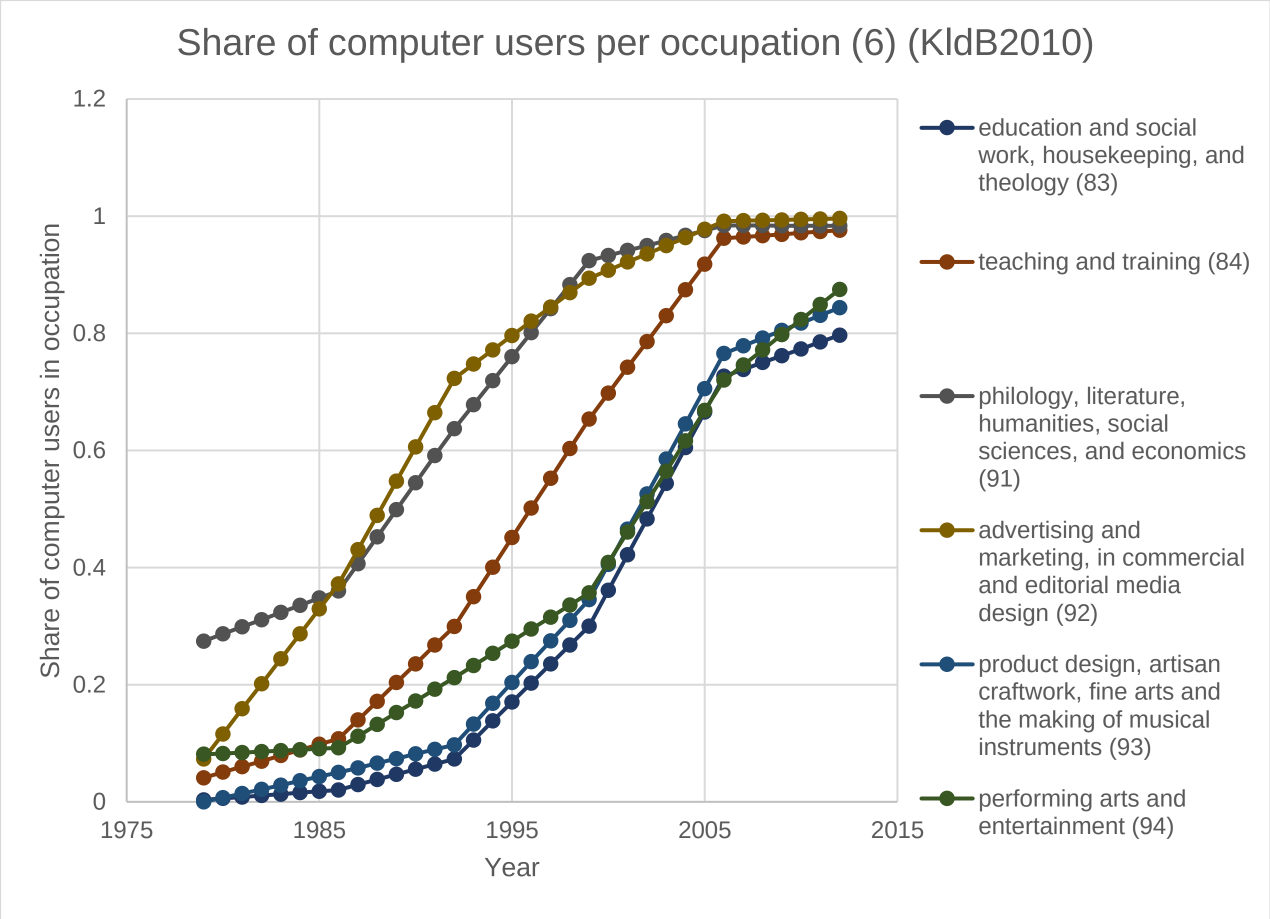

Figure A6: *Share of computer users per occupation (6) (KldB2010)*

Note: Yearly share of computer users for KldB2010 83-94, based on based on Table A11 to Table A15 in Appendix A5.iv.

A5.iv. Technological progression according to *BIBB Data* using *KldB2010* – full tables

Table A11: *Share of computer users per occupation per year, 1979-1985, KldB2010*

KldB2010	Wave						
	1979	1980	1981	1982	1983	1984	1985
agriculture (11)	0.005	0.007	0.009	0.011	0.013	0.015	0.017
gardening (12)	0	0.004	0.007	0.011	0.014	0.018	0.021
raw_material_prod (21)	0.012	0.012	0.012	0.012	0.012	0.012	0.012
plastic_wood_process (22)	0	0.003	0.005	0.008	0.01	0.013	0.015
paper_process (23)	0.052	0.061	0.069	0.078	0.087	0.096	0.104
metal_making (24)	0.005	0.008	0.012	0.016	0.019	0.023	0.026
machine_car_build (25)	0.038	0.048	0.058	0.068	0.078	0.088	0.098
electrical_engineer (26)	0.134	0.162	0.19	0.219	0.247	0.275	0.303
tech_research_construction (27)	0.081	0.112	0.144	0.175	0.206	0.238	0.269
textile_process (28)	0.003	0.004	0.005	0.007	0.008	0.009	0.011
food_process (29)	0.005	0.006	0.007	0.009	0.01	0.011	0.013
architecture (31)	0.133	0.162	0.191	0.22	0.249	0.278	0.307
construction (32)	0	0.002	0.003	0.005	0.007	0.008	0.01
interior_constr (33)	0	9E-04	0.002	0.003	0.004	0.005	0.005
build_engineer (34)	0.003	0.007	0.012	0.017	0.021	0.026	0.031
math_bio_chem (41)	0.098	0.125	0.152	0.179	0.205	0.232	0.259
geo (42)	0	0.011	0.021	0.032	0.042	0.053	0.063
IT (43)	0.869	0.876	0.883	0.889	0.896	0.903	0.91
logistics (51)	0.032	0.043	0.054	0.065	0.076	0.087	0.098
drivers (52)	0.009	0.011	0.012	0.014	0.016	0.018	0.019
safety (53)	0.066	0.085	0.105	0.124	0.144	0.163	0.183
cleaning_service (54)	0	6E-04	0.001	0.002	0.002	0.003	0.003
purchasing_sales (61)	0.047	0.072	0.097	0.122	0.148	0.173	0.198
retail (62)	0.018	0.024	0.031	0.037	0.044	0.05	0.057
tourism (63)	0.034	0.039	0.045	0.051	0.057	0.063	0.068
management (71)	0.089	0.125	0.162	0.198	0.234	0.27	0.307
finance (72)	0.218	0.275	0.333	0.39	0.447	0.504	0.561
law (73)	0.112	0.138	0.163	0.188	0.213	0.239	0.264
medical (81)	0.036	0.045	0.053	0.062	0.07	0.079	0.087
wellness (82)	0.003	0.006	0.008	0.011	0.014	0.017	0.02
education (83)	0.003	0.006	0.008	0.011	0.013	0.015	0.018
teaching (84)	0.041	0.05	0.06	0.07	0.079	0.089	0.098
social_science (91)	0.274	0.287	0.299	0.311	0.323	0.336	0.348
marketing (92)	0.073	0.116	0.159	0.201	0.244	0.287	0.329
craftwork (93)	0	0.007	0.014	0.021	0.029	0.036	0.043
entertainment (94)	0.081	0.083	0.084	0.086	0.087	0.089	0.091

Note: The waves providing the computer use data are marked by “wave”. Computer use progression between the waves is assumed to be linear.

Table A12: *Share of computer users per occupation per year, 1986-1991, KldB2010*

KldB2010	Wave					
	1986	1987	1988	1989	1990	1991
agriculture (11)	0.019	0.031	0.043	0.055	0.067	0.08
gardening (12)	0.025	0.029	0.033	0.037	0.041	0.044
raw_material_prod (21)	0.011	0.024	0.036	0.048	0.06	0.072
plastic_wood_process (22)	0.018	0.032	0.046	0.06	0.074	0.088
paper_process (23)	0.113	0.147	0.18	0.213	0.247	0.28
metal_making (24)	0.03	0.042	0.054	0.066	0.078	0.09
machine_car_build (25)	0.109	0.122	0.135	0.148	0.161	0.174
electrical_engineer (26)	0.331	0.339	0.347	0.355	0.363	0.37
tech_research_construction (27)	0.3	0.342	0.384	0.426	0.468	0.509
textile_process (28)	0.012	0.016	0.02	0.024	0.028	0.032
food_process (29)	0.014	0.019	0.023	0.028	0.032	0.037
architecture (31)	0.335	0.377	0.418	0.459	0.501	0.542
construction (32)	0.012	0.016	0.02	0.024	0.029	0.033
interior_constr (33)	0.006	0.013	0.021	0.028	0.035	0.042
build_engineer (34)	0.035	0.044	0.052	0.061	0.07	0.078
math_bio_chem (41)	0.286	0.311	0.336	0.361	0.386	0.411
geo (42)	0.074	0.147	0.22	0.293	0.366	0.439
IT (43)	0.916	0.921	0.926	0.93	0.935	0.94
logistics (51)	0.11	0.124	0.138	0.152	0.166	0.18
drivers (52)	0.021	0.024	0.028	0.031	0.034	0.037
safety (53)	0.202	0.231	0.259	0.287	0.315	0.344
cleaning_service (54)	0.004	0.004	0.005	0.005	0.006	0.006
purchasing_sales (61)	0.224	0.267	0.31	0.352	0.395	0.438
retail (62)	0.063	0.076	0.09	0.103	0.116	0.129
tourism (63)	0.074	0.088	0.102	0.116	0.13	0.144
management (71)	0.343	0.39	0.437	0.485	0.532	0.579
finance (72)	0.619	0.647	0.676	0.705	0.733	0.762
law (73)	0.289	0.335	0.38	0.425	0.471	0.516
medical (81)	0.096	0.123	0.151	0.178	0.206	0.233
wellness (82)	0.023	0.03	0.037	0.043	0.05	0.057
education (83)	0.02	0.029	0.038	0.047	0.056	0.064
teaching (84)	0.108	0.14	0.172	0.204	0.235	0.267
social_science (91)	0.36	0.406	0.452	0.499	0.545	0.591
marketing (92)	0.372	0.43	0.489	0.547	0.606	0.664
craftwork (93)	0.05	0.058	0.066	0.074	0.082	0.09
entertainment (94)	0.092	0.112	0.132	0.152	0.172	0.192

Note: The waves providing the computer use data are marked by "wave". Computer use progression between the waves is assumed to be linear.

Table A13: *Share of computer users per occupation per year, 1992-1998, KldB2010*

KldB2010	Wave						
	1992	1993	1994	1995	1996	1997	1998
agriculture (11)	0.092	0.1	0.107	0.115	0.123	0.131	0.139
gardening (12)	0.048	0.056	0.064	0.072	0.08	0.088	0.096
raw_material_prod (21)	0.085	0.089	0.094	0.099	0.104	0.109	0.114
plastic_wood_process (22)	0.102	0.111	0.12	0.129	0.138	0.148	0.157
paper_process (23)	0.314	0.334	0.354	0.374	0.394	0.415	0.435
metal_making (24)	0.102	0.112	0.121	0.13	0.139	0.148	0.157
machine_car_build (25)	0.187	0.207	0.228	0.248	0.268	0.289	0.309
electrical_engineer (26)	0.378	0.402	0.426	0.449	0.473	0.497	0.521
tech_research_construction (27)	0.551	0.587	0.623	0.658	0.694	0.73	0.765
textile_process (28)	0.036	0.046	0.055	0.065	0.075	0.084	0.094
food_process (29)	0.041	0.049	0.057	0.065	0.073	0.081	0.089
architecture (31)	0.583	0.625	0.667	0.709	0.752	0.794	0.836
construction (32)	0.037	0.038	0.039	0.04	0.04	0.041	0.042
interior_constr (33)	0.049	0.056	0.063	0.07	0.077	0.084	0.091
build_engineer (34)	0.087	0.099	0.11	0.122	0.134	0.145	0.157
math_bio_chem (41)	0.436	0.471	0.505	0.54	0.575	0.61	0.645
geo (42)	0.513	0.559	0.605	0.651	0.697	0.743	0.789
IT (43)	0.944	0.947	0.949	0.952	0.954	0.957	0.96
logistics (51)	0.194	0.219	0.244	0.269	0.294	0.319	0.344
drivers (52)	0.04	0.045	0.049	0.053	0.057	0.061	0.065
safety (53)	0.372	0.413	0.453	0.494	0.534	0.575	0.615
cleaning_service (54)	0.006	0.008	0.009	0.01	0.011	0.012	0.014
purchasing_sales (61)	0.481	0.523	0.565	0.606	0.648	0.69	0.732
retail (62)	0.142	0.166	0.19	0.214	0.238	0.262	0.286
tourism (63)	0.157	0.181	0.205	0.229	0.253	0.277	0.301
management (71)	0.626	0.664	0.701	0.739	0.776	0.813	0.851
finance (72)	0.791	0.817	0.844	0.871	0.898	0.925	0.951
law (73)	0.562	0.611	0.659	0.708	0.757	0.806	0.855
medical (81)	0.261	0.309	0.358	0.406	0.455	0.503	0.552
wellness (82)	0.064	0.086	0.108	0.13	0.152	0.174	0.197
education (83)	0.073	0.106	0.138	0.17	0.203	0.235	0.268
teaching (84)	0.299	0.35	0.401	0.451	0.502	0.552	0.603
social_science (91)	0.637	0.678	0.719	0.76	0.801	0.842	0.883
marketing (92)	0.723	0.747	0.772	0.796	0.821	0.845	0.869
craftwork (93)	0.097	0.133	0.168	0.204	0.239	0.275	0.31
entertainment (94)	0.212	0.233	0.253	0.274	0.295	0.315	0.336

Note: The waves providing the computer use data are marked by “wave”. Computer use progression between the waves is assumed to be linear.

Table A14: *Share of computer users per occupation per year, 1999-2005, KldB2010*

KldB2010	Wave						
	1999	2000	2001	2002	2003	2004	2005
agriculture (11)	0.147	0.217	0.286	0.355	0.425	0.494	0.564
gardening (12)	0.104	0.154	0.205	0.256	0.307	0.357	0.408
raw_material_prod (21)	0.118	0.177	0.235	0.294	0.352	0.41	0.469
plastic_wood_process (22)	0.166	0.236	0.307	0.378	0.448	0.519	0.589
paper_process (23)	0.455	0.51	0.565	0.619	0.674	0.729	0.783
metal_making (24)	0.167	0.246	0.325	0.404	0.483	0.562	0.641
machine_car_build (25)	0.33	0.405	0.481	0.557	0.632	0.708	0.784
electrical_engineer (26)	0.544	0.595	0.646	0.697	0.748	0.799	0.85
tech_research_construction (27)	0.801	0.821	0.841	0.861	0.882	0.902	0.922
textile_process (28)	0.103	0.157	0.21	0.264	0.317	0.371	0.424
food_process (29)	0.097	0.139	0.181	0.223	0.264	0.306	0.348
architecture (31)	0.878	0.895	0.911	0.928	0.945	0.962	0.979
construction (32)	0.042	0.075	0.108	0.141	0.173	0.206	0.239
interior_constr (33)	0.098	0.142	0.186	0.23	0.274	0.319	0.363
build_engineer (34)	0.169	0.228	0.288	0.348	0.408	0.467	0.527
math_bio_chem (41)	0.68	0.719	0.758	0.797	0.837	0.876	0.915
geo (42)	0.835	0.854	0.873	0.891	0.91	0.929	0.947
IT (43)	0.962	0.968	0.973	0.978	0.984	0.989	0.995
logistics (51)	0.369	0.419	0.468	0.517	0.567	0.616	0.665
drivers (52)	0.069	0.111	0.153	0.196	0.238	0.28	0.322
safety (53)	0.656	0.694	0.731	0.769	0.807	0.845	0.882
cleaning_service (54)	0.015	0.027	0.04	0.052	0.065	0.077	0.089
purchasing_sales (61)	0.774	0.801	0.829	0.857	0.885	0.913	0.941
retail (62)	0.31	0.361	0.411	0.462	0.513	0.564	0.615
tourism (63)	0.325	0.363	0.401	0.439	0.477	0.515	0.553
management (71)	0.888	0.902	0.915	0.929	0.943	0.957	0.97
finance (72)	0.978	0.981	0.984	0.986	0.989	0.992	0.994
law (73)	0.904	0.917	0.93	0.943	0.956	0.969	0.981
medical (81)	0.6	0.643	0.685	0.728	0.77	0.812	0.855
wellness (82)	0.219	0.263	0.308	0.353	0.398	0.443	0.488
education (83)	0.3	0.361	0.422	0.483	0.544	0.605	0.666
teaching (84)	0.654	0.698	0.742	0.786	0.83	0.874	0.918
social_science (91)	0.924	0.933	0.941	0.95	0.958	0.967	0.976
marketing (92)	0.894	0.908	0.922	0.936	0.95	0.964	0.977
craftwork (93)	0.345	0.405	0.465	0.525	0.585	0.645	0.705
entertainment (94)	0.357	0.409	0.46	0.512	0.564	0.616	0.668

Note: The waves providing the computer use data are marked by "wave". Computer use progression between the waves is assumed to be linear.

Table A15: *Share of computer users per occupation per year, 2006-2012, KldB2010*

KldB2010	Wave 2006	2007	2008	2009	2010	2011	Wave 2012
agriculture (11)	0.633	0.654	0.676	0.697	0.718	0.739	0.761
gardening (12)	0.459	0.455	0.451	0.446	0.442	0.438	0.434
raw_material_prod (21)	0.527	0.559	0.591	0.622	0.654	0.685	0.717
plastic_wood_process (22)	0.66	0.659	0.658	0.658	0.657	0.656	0.656
paper_process (23)	0.838	0.848	0.857	0.867	0.877	0.886	0.896
metal_making (24)	0.72	0.725	0.73	0.735	0.74	0.745	0.75
machine_car_build (25)	0.86	0.858	0.856	0.854	0.852	0.85	0.848
electrical_engineer (26)	0.901	0.903	0.904	0.906	0.907	0.909	0.91
tech_research_construction (27)	0.942	0.947	0.952	0.957	0.962	0.967	0.972
textile_process (28)	0.478	0.501	0.525	0.548	0.572	0.595	0.619
food_process (29)	0.39	0.419	0.448	0.477	0.506	0.534	0.563
architecture (31)	0.996	0.992	0.989	0.985	0.982	0.978	0.975
construction (32)	0.271	0.294	0.317	0.34	0.363	0.385	0.408
interior_constr (33)	0.407	0.414	0.421	0.428	0.436	0.443	0.45
build_engineer (34)	0.587	0.593	0.6	0.606	0.612	0.619	0.625
math_bio_chem (41)	0.954	0.951	0.948	0.945	0.942	0.939	0.936
geo (42)	0.966	0.965	0.964	0.963	0.963	0.962	0.961
IT (43)	1	1	1	1	1	1	1
logistics (51)	0.714	0.717	0.719	0.721	0.723	0.725	0.727
drivers (52)	0.364	0.376	0.388	0.4	0.413	0.425	0.437
safety (53)	0.92	0.921	0.922	0.922	0.923	0.924	0.924
cleaning_service (54)	0.102	0.111	0.12	0.13	0.139	0.148	0.157
purchasing_sales (61)	0.969	0.97	0.972	0.973	0.975	0.976	0.978
retail (62)	0.665	0.673	0.68	0.687	0.694	0.701	0.708
tourism (63)	0.59	0.606	0.622	0.637	0.653	0.669	0.684
management (71)	0.984	0.985	0.986	0.986	0.987	0.988	0.989
finance (72)	0.997	0.997	0.997	0.998	0.998	0.998	0.998
law (73)	0.994	0.994	0.994	0.993	0.993	0.992	0.992
medical (81)	0.897	0.903	0.909	0.915	0.921	0.927	0.933
wellness (82)	0.533	0.557	0.582	0.607	0.631	0.656	0.68
education (83)	0.727	0.738	0.75	0.762	0.773	0.785	0.797
teaching (84)	0.962	0.964	0.967	0.969	0.971	0.974	0.976
social_science (91)	0.984	0.984	0.984	0.984	0.984	0.983	0.983
marketing (92)	0.991	0.992	0.993	0.994	0.994	0.995	0.996
craftwork (93)	0.765	0.778	0.792	0.805	0.818	0.831	0.844
entertainment (94)	0.72	0.746	0.772	0.798	0.823	0.849	0.875

Note: The waves providing the computer use data are marked by “wave”. Computer use progression between the waves is assumed to be linear.

A6. Industry classification *W_93*

The W93 industry classifications are ordered into sections provided in *Table A16*. This thesis uses the 93 industry classification instead of the newer W2003 or W2008 as the W93 were part of the *SIAB Data*. Generall, some *KldB88* occupations have significant overlap with the W93 but *KldB88* occupations can be part of multiple W93 industries.

Table A16: *W93 industry classification number, code and name*

W93 Industries		
Number	Code	Name
1	(A,B,C)	Agriculture, Fishing, Mining
2	(DD,DF,DG,DH)	Wood manufacturing, Fuel manufacturing, Chemical manufacturing, Rubber manufacturing
3	(DJ,DK)	Metal manufacturing, Machine manufacturing
4	(DL,DM)	Office machine manufacturing, Motor vehicle manufacturing
5	(DA,DB,DC,DE,DI,DN)	Food manufacturing, Textile manufacturing, Leather manufacturing, Paper manufacturing, Glass manufacturing, Furniture manufacturing
6	(H)	Hotels and Restaurants
7	(F)	Construction
8	(G)	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
9	(I)	Transport, storage and communication
10	(J,K)	Financial intermediation, real estate, renting and business activities
11	(E,O,P)	Electricity, gas and water supply, Other community, social and personal service activities, Private households with employed persons
12	(M,N)	Education, Health and social work
13	(L,Q)	Public administration and defense; compulsory social security, Extra-territorial organizations and bodies

Note: This grouping is given by the SIAB Data.

A7. *SIAB Data* in depth descriptive statistics *wage analysis*

This section includes a description of the panel structure of the *SIAB Data,* as well as observation tables for the explanatory variables for the *wage analysis*.

Table A17: *Description of the panel structure of the SIAB Data*

```
personnumber:  1, 3, ..., 1707228                          n =     971510
    year:  1979, 1980, ..., 2006                           T =         28
           Delta(year) = 1 unit
           Span(year)  = 28 periods
           (personnumber*year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         1       2       5        10        16      27      28

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+------------------------------
    37253      3.83    3.83 |  1111111111111111111111111111
    30401      3.13    6.96 |  .............111111111111111
    14286      1.47    8.43 |  11..........................
    13426      1.38    9.82 |  111.........................
    12639      1.30   11.12 |  1111........................
    11941      1.23   12.35 |  11111.......................
    11292      1.16   13.51 |  111111......................
    11257      1.16   14.67 |  ..........................11
     9771      1.01   15.67 |  1111111.....................
   819244     84.33  100.00 | (other patterns)
 ---------------------------+------------------------------
   971510    100.00         |  XXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

Table A18: *Observations per age*

Age	Freq.	Percent	Cum.
17	16,835	0.15	0.15
18	48,338	0.44	0.59
19	110,507	1	1.6
20	175,320	1.59	3.19
21	224,919	2.04	5.23
22	258,898	2.35	7.58
23	279,550	2.54	10.12
24	292,418	2.66	12.77
25	299,685	2.72	15.5
26	305,469	2.77	18.27
27	310,477	2.82	21.09
28	313,581	2.85	23.94
29	316,262	2.87	26.81
30	316,597	2.87	29.68
31	315,799	2.87	32.55
32	314,615	2.86	35.41
33	312,806	2.84	38.25
34	309,443	2.81	41.06
35	307,848	2.8	43.85
36	305,660	2.78	46.63
37	303,117	2.75	49.38
38	301,743	2.74	52.12
39	300,648	2.73	54.85
40	299,331	2.72	57.57
41	296,513	2.69	60.26
42	293,244	2.66	62.93
43	288,776	2.62	65.55
44	283,249	2.57	68.12
45	277,324	2.52	70.64
46	269,334	2.45	73.08
47	261,567	2.38	75.46
48	255,105	2.32	77.78
49	249,246	2.26	80.04
50	242,873	2.21	82.25
51	236,919	2.15	84.4
52	230,532	2.09	86.49
53	223,295	2.03	88.52
54	215,338	1.96	90.47
55	204,257	1.85	92.33
56	184,963	1.68	94.01
57	168,603	1.53	95.54
58	149,628	1.36	96.9
59	125,721	1.14	98.04
60	103,214	0.94	98.98
61	64,725	0.59	99.56
62	47,993	0.44	100
Total	11,012,285	100	

Table A19: *Observations and levels of the "Employment Complexity" variable*

Employment Complexity	Freq.	Percent	Cum.
1 Assistant Employment	412,821	3.75	3.75
2 Professional Employment	8,689,279	78.91	82.65
3 Complex Sepcialist Employment	957,012	8.69	91.34
4 Highly complex Expert Employment	953,173	8.66	100
Total	11,012,285	100	

Table A20: *Observations and levels of the "Vocational Training" variable*

Vocational Training	Freq.	Percent	Cum.
No Training	1,474,115	13.39	13.39
Vocational Training	7,975,931	72.43	85.81
Highschool	138,661	1.26	87.07
Highschool and Vocational Training	446,679	4.06	91.13
University	976,899	8.87	100
Total	11,012,285	100	

Table A21: *Observations per State*

State	Freq.	Percent	Cum.
Schleswig_Holstein	332,635	3.02	3.02
Hamburg	339,201	3.08	6.1
Niedersachsen	987,431	8.97	15.07
Bremen	130,085	1.18	16.25
Nordrhein_Westfalen	2,614,818	23.74	39.99
Hessen	945,747	8.59	48.58
Pheinland_Pfalz	503,647	4.57	53.15
Baden_Würtemberg	1,659,101	15.07	68.22
Bayern	1,817,236	16.5	84.72
Saarland	159,043	1.44	86.17
Berlin	430,821	3.91	90.08
Brandenburg	196,958	1.79	91.87
Mecklenburg_Vorpommern	136,656	1.24	93.11
Sachsen	356,905	3.24	96.35
Sachsen_Anhalt	208,867	1.9	98.25
Thüringen	193,134	1.75	100
Total	11,012,285	100	

Table A22: *Observations per W93 Industry*

W93 Industry	Freq.	Percent	Cum.
1 (A,B,C) Agriculture, Fishing, Mining	238,949	2.17	2.17
2 (DD,DF,DG,DH) Wood manufacturing, Fuel manufacturing, Chemical manufacturing, Rubber manufacturing	552,139	5.01	7.18
3 (DJ,DK) Metal manufacturing, Machine manufacturing	1,185,921	10.77	17.95
4 (DL,DM) Office machine manufacturing, Motor vehicle manufacturing	982,191	8.92	26.87
5 (DA,DB,DC,DE,DI,DN) Food manufacturing, Textile manufacturing, Leather manufacturing, Paper manufacturing, Glass manufacturing, Furniture manufacturing	1,104,583	10.03	36.9
6 (H) Hotels and Restaurants	155,272	1.41	38.31
7 (F) Construction	1,093,163	9.93	48.24
8 (G) Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	1,636,965	14.86	63.1
9 (I) Transport, storage and communication	618,682	5.62	68.72
10 (J,K) Financial intermediation, real estate, renting and business activities	1,318,599	11.97	80.7
11 (E,O,P) Electricity, gas and water supply, Other community, social and personal service activities, Private households with employed persons	451,845	4.1	84.8
12 (M,N) Education, Health and social work	979,941	8.9	93.7
13 (L,Q) Public administration and defense; compulsory social security, Extra-territorial organizations and bodies	694,035	6.3	100
Total	11,012,285	100	

Table A23: *Observations per year of experience in occupation*

experience	Freq.	Percent	Cum.
1	1,596,140	14.51	14.51
2	1,278,220	11.62	26.12
3	1,040,000	9.45	35.57
4	892,881	8.11	43.69
5	781,844	7.11	50.79
6	688,789	6.26	57.05
7	609,064	5.54	62.59
8	540,207	4.91	67.5
9	480,196	4.36	71.86
10	427,326	3.88	75.75
11	380,651	3.46	79.21
12	339,450	3.09	82.29
13	301,336	2.74	85.03
14	265,963	2.42	87.45
15	231,407	2.1	89.55
16	189,907	1.73	91.28
17	164,330	1.49	92.77
18	142,684	1.3	94.07
19	123,611	1.12	95.19
20	106,874	0.97	96.16
21	91,961	0.84	97
22	78,159	0.71	97.71
23	66,048	0.6	98.31
24	55,462	0.5	98.81
25	45,929	0.42	99.23
26	36,977	0.34	99.57
27	28,564	0.26	99.83
28	19,249	0.17	100
Total	11,012,285	100	

A8. *SIAB Data* in depth descriptive statistics *occupation change analysis*

Table A24: *Descriptive statistics SIAB Data, occupation change data differences*

Variable		Mean	Std. Dev.	Min	Max	Observations	
personnumber	overall	854019.9	493141.9	1	1707228	N =	11003229
	between		493021.1	1	1707228	n =	970655
	within		0	854019.9	854019.9	T-bar =	11.3359
formerjobs	overall	2.969299	2.698495	1	148	N =	11003229
	between		2.136633	1	91.21429	n =	970655
	within		1.365892	-41.1484	65.38597	T-bar =	11.3359
female	overall	0.333776	0.471561	0	1	N =	11003229
	between		0.490539	0	1	n =	970655
	within		0	0.333776	0.333776	T-bar =	11.3359
german	overall	0.911248	0.284385	0	1	N =	9523159
	between		0.308125	0	1	n =	802046
	within		0.082718	-0.05304	1.875534	T-bar =	11.8736
daily_wage	overall	68.29136	31.13097	1	172	N =	11003229
	between		25.38478	1	172	n =	970655
	within		19.34096	-68.8086	210.7529	T-bar =	11.3359
lvl_of_performance	overall	2.221213	0.647228	1	4	N =	11003229
	between		0.598723	1	4	n =	970655
	within		0.282481	-0.67164	5.11407	T-bar =	11.3359
days_unemployed	overall	4.583963	49.90307	0	8400	N =	11003229
	between		42.57068	0	4930.95	n =	970655
	within		43.22023	-4602.72	5618.87	T-bar =	11.3359
industry	overall	7.310686	3.38715	1	13	N =	11003229
	between		3.085876	1	13	n =	970655
	within		1.385994	-4.26074	18.88211	T-bar =	11.3359
year	overall	1993.028	7.854966	1979	2006	N =	11003229
	between		7.069496	1979	2006	n =	970655
	within		5.605881	1972.028	2014.028	T-bar =	11.3359

Variable		Mean	Std. Dev.	Min	Max	Observations	
vocTrain	overall	2.223011	1.024968	1	5	N =	11003229
	between		1.000893	1	5	n =	970655
	within		0.305982	-1.63413	6.080154	T-bar =	11.3359
age	overall	38.30439	11.25113	17	62	N =	11003229
	between		11.34463	17	62	n =	970655
	within		5.605881	17.30439	59.30439	T-bar =	11.3359
ln_wage	overall	4.138866	0.537496	0	7.386433	N =	11003229
	between		0.481948	0	5.995191	n =	970655
	within		0.324116	-0.86561	6.966645	T-bar =	11.3359
KldB88	overall	20.07031	8.278418	1	31	N =	11003229
	between		7.712233	1	31	n =	970655
	within		3.265767	-8.81858	48.49136	T-bar =	11.3359
employment_change	overall	0.028637	0.18818	-0.7	0.92	N =	11003229
	between		0.100217	-0.7	0.92	n =	970655
	within		0.169836	-0.8647	1.121494	T-bar =	11.3359
ln_compute-ruse_change	overall	0.206079	0.186085	-0.64226	0.689367	N =	11003229
(tech_age)	between		0.13944	-0.41855	0.667574	n =	970655
	within		0.129834	-0.39773	0.860666	T-bar =	11.3359
experience	overall	7.111178	5.86878	1	28	N =	11003229
	between		3.420492	1	16	n =	970655
	within		4.594367	-6.38882	20.61118	T-bar =	11.3359
ln_age	overall	3.599829	0.308131	2.833213	4.127134	N =	11003229
	between		0.313102	2.833213	4.127134	n =	970655
	within		0.158299	2.829621	4.30066	T-bar =	11.3359
ln_lvl_of_performance	overall	0.761952	0.26232	0	1.386294	N =	11003229
	between		0.241453	0	1.386294	n =	970655
	within		0.122661	-0.57483	2.098736	T-bar =	11.3359
ln_formerjobs	overall	0.806731	0.720477	0	4.997212	N =	11003229
	between		0.615349	0	4.471099	n =	970655
	within		0.351672	-2.59599	3.113443	T-bar =	11.3359
ln_experience	overall	1.579927	0.93413	0	3.332205	N =	11003229
	between		0.639931	0	2.668673	n =	970655
	within		0.751882	-0.84471	3.128157	T-bar =	11.3359
ln_voc_Train	overall	0.713785	0.399258	0	1.609438	N =	11003229
	between		0.397799	0	1.609438	n =	970655
	within		0.124844	-0.83817	2.265743	T-bar =	11.3359

Variable		Mean	Std. Dev.	Min	Max	Observations
state	overall	7.090525	3.332806	1	16	N =11003229
	between		3.453874	1	16	n = 970655
	within		0.795137	-6.97198	21.18143	T-bar = 11.3359

Note: Where applicable, overall, between and within mean, standard deviation, minimum and maximum per variable as well as number of observations including the variable, number of persons with value for the variable and average number of observations of the variable for one person.

Table A25: *Description of the panel structure of the SIAB Data, occupation change data differences*

```
personnumber:  1, 3, ..., 1707228                              n =     958999
    year:  1979, 1980, ..., 2006                               T =         28
           Delta(year) = 1 unit
           Span(year)  = 28 periods
           (personnumber*year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         1       2       5        10        16      27      28

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+-----------------------------
     34544      3.60    3.60 |  1111111111111111111111111111
     27556      2.87    6.48 |  .............111111111111111
     14096      1.47    7.95 |  11..........................
     13707      1.43    9.37 |  111.........................
     12578      1.31   10.69 |  1111........................
     11726      1.22   11.91 |  11111.......................
     11224      1.17   13.08 |  ..........................11
     11188      1.17   14.25 |  111111......................
      9332      0.97   15.22 |  1111111.....................
    813048     84.78  100.00 | (other patterns)
 ---------------------------+-----------------------------
    958999    100.00         |  XXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

Table A26: *Observations per KldB88, occupation change data differences*

KldB88	Freq.	Percent	Cum.
1	193,449	1.75	1.75
2	77,847	0.71	2.46
4	38,872	0.35	2.81
5	249,266	2.26	5.07
6	153,505	1.39	6.46
7	39,128	0.35	6.82
8	360,141	3.26	10.08
9	957,593	8.68	18.76
10	346,728	3.14	21.91
11	286,469	2.6	24.5
12	163,088	1.48	25.98
14	340,101	3.08	29.07
15	532,943	4.83	33.9
16	113,905	1.03	34.93
17	130,170	1.18	36.11
18	139,242	1.26	37.37
19	219,532	1.99	39.36
21	122,912	1.11	40.48
22	322,068	2.92	43.4
23	580,047	5.26	48.66
24	807,152	7.32	55.97
25	458,121	4.15	60.13
26	980,029	8.88	69.01
27	2,225,608	20.18	89.19
28	178,619	1.62	90.81
29	107,484	0.97	91.78
30	570,749	5.17	96.96
31	335,783	3.04	100
Total	11,030,551	100	

Table A27: *Observations per age, occupation change data differences*

Age	Freq.	Percent	Cum.
17	16,753	0.15	0.15
18	47,912	0.43	0.59
19	109,238	0.99	1.58
20	173,994	1.58	3.15
21	223,925	2.03	5.18
22	258,156	2.34	7.52
23	279,096	2.53	10.05
24	292,676	2.65	12.71
25	300,361	2.72	15.43
26	306,703	2.78	18.21
27	311,994	2.83	21.04
28	315,301	2.86	23.9
29	318,050	2.88	26.78
30	318,346	2.89	29.67
31	317,689	2.88	32.55
32	316,334	2.87	35.42
33	314,266	2.85	38.26
34	310,525	2.82	41.08
35	308,696	2.8	43.88
36	306,024	2.77	46.65
37	303,181	2.75	49.4
38	301,528	2.73	52.13
39	300,114	2.72	54.86
40	298,522	2.71	57.56
41	295,584	2.68	60.24
42	292,325	2.65	62.89
43	287,857	2.61	65.5
44	282,365	2.56	68.06
45	276,483	2.51	70.57
46	268,646	2.44	73
47	261,007	2.37	75.37
48	254,645	2.31	77.68
49	249,035	2.26	79.94
50	242,805	2.2	82.14
51	236,974	2.15	84.29
52	230,788	2.09	86.38
53	223,863	2.03	88.41
54	216,088	1.96	90.37
55	205,085	1.86	92.23
56	186,344	1.69	93.91
57	170,285	1.54	95.46
58	151,659	1.37	96.83
59	128,132	1.16	97.99
60	105,855	0.96	98.95
61	66,343	0.6	99.56
62	48,999	0.44	100
Total	11,030,551	100	

Table A28: *Observations and levels of the "Employment Complexity" variable, occupation change data differences*

Employment Complexity	Freq.	Percent	Cum.
1 Assistant Employment	417,423	3.78	3.78
2 Professional Employment	8,711,412	78.98	82.76
3 Complex Sepcialist Employment	956,672	8.67	91.43
4 Highly complex Expert Employment	945,044	8.57	100
Total	11,030,551	100	

Table A29: *Observations and levels of the "Vocational Training" variable, occupation change data differences*

Vocational Training	Freq.	Percent	Cum.
No Training	1,484,587	13.46	13.46
Vocational Training	7,881,834	71.45	84.91
Highschool	203,865	1.85	86.76
Highschool and Vocational Training	463,295	4.2	90.96
University	996,970	9.04	100
Total	11,030,551	100	

Table A30*: Observations per State, occupation change data differences*

State	Freq.	Percent	Cum.
Schleswig_Holstein	333,171	3.02	3.02
Hamburg	340,254	3.08	6.11
Niedersachsen	989,578	8.97	15.08
Bremen	130,269	1.18	16.26
Nordrhein_Westfalen	2,621,445	23.77	40.02
Hessen	948,188	8.6	48.62
Pheinland_Pfalz	504,958	4.58	53.2
Baden_Würtemberg	1,665,707	15.1	68.3
Bayern	1,824,563	16.54	84.84
Saarland	159,258	1.44	86.28
Berlin	429,523	3.89	90.18
Brandenburg	195,192	1.77	91.95
Mecklenburg_Vorpommern	135,438	1.23	93.17
Sachsen	354,140	3.21	96.38
Sachsen_Anhalt	207,100	1.88	98.26
Thüringen	191,767	1.74	100
Total	11,030,551	100	

Table A31: *Observations per W93 Industry, occupation change data differences*

W93 Industry	Freq.	Percent	Cum.
1 (A,B,C) Agriculture, Fishing, Mining	238,753	2.16	2.16
2 (DD,DF,DG,DH) Wood manufacturing, Fuel manufacturing, Chemical manufacturing, Rubber manufacturing	553,576	5.02	7.18
3 (DJ,DK) Metal manufacturing, Machine manufacturing	1,188,196	10.77	17.95
4 (DL,DM) Office machine manufacturing, Motor vehicle manufacturing	986,004	8.94	26.89
5 (DA,DB,DC,DE,DI,DN) Food manufacturing, Textile manufacturing, Leather manufacturing, Paper manufacturing, Glass manufacturing, Furniture manufacturing	1,109,639	10.06	36.95
6 (H) Hotels and Restaurants	154,008	1.4	38.35
7 (F) Construction	1,087,852	9.86	48.21
8 (G) Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	1,641,179	14.88	63.09
9 (I) Transport, storage and communication	618,896	5.61	68.7
10 (J,K) Financial intermediation, real estate, renting and business activities	1,317,380	11.94	80.64
11 (E,O,P) Electricity, gas and water supply, Other community, social and personal service activities, Private households with employed persons	451,178	4.09	84.73
12 (M,N) Education, Health and social work	986,057	8.94	93.67
13 (L,Q) Public administration and defense; compulsory social security, Extra-territorial organizations and bodies	697,833	6.33	100
Total	11,030,551	100	

Table A32: *Observations per year of experience in occupation, occupation change data differences*

Experience	Freq.	Percent	Cum.
1	1,553,821	14.09	14.09
2	1,279,365	11.6	25.68
3	1,042,841	9.45	35.14
4	896,484	8.13	43.27
5	785,982	7.13	50.39
6	693,598	6.29	56.68
7	613,685	5.56	62.24
8	545,626	4.95	67.19
9	485,324	4.4	71.59
10	432,390	3.92	75.51
11	385,246	3.49	79
12	343,650	3.12	82.12
13	305,137	2.77	84.88
14	269,429	2.44	87.33
15	234,522	2.13	89.45
16	193,082	1.75	91.2
17	166,314	1.51	92.71
18	144,243	1.31	94.02
19	124,912	1.13	95.15
20	107,980	0.98	96.13
21	92,904	0.84	96.97
22	79,000	0.72	97.69
23	66,722	0.6	98.29
24	56,014	0.51	98.8
25	46,408	0.42	99.22
26	37,409	0.34	99.56
27	28,900	0.26	99.82
28	19,563	0.18	100
Total	11,030,551	100	

A9. *SIAB Data* in depth descriptive statistics *wage analysis*, *KldB2010*

Table A33: *Descriptive statistics SIAB Data, wage data KldB2010*

Variable		Mean	Std. Dev.	Min	Max	Observations
personnumber	overall	853924.8	493093.2	1	1707228	N =11597284
	between		492918.8	1	1707228	n = 1027186
	within		0	853924.8	853924.8	T-bar = 11.2903
formerjobs	overall	2.976364	2.707928	1	148	N =11597284
	between		2.097442	1	90.78571	n = 1027186
	within		1.384938	-44.9184	65.39303	T-bar = 11.2903
female	overall	0.350831	0.47723	0	1	N =11597284
	between		0.493451	0	1	n = 1027186
	within		0	0.350831	0.350831	T-bar = 11.2903
german	overall	0.905705	0.292239	0	1	N =10020811
	between		0.314601	0	1	n = 848611
	within		0.085964	-0.05858	1.86999	T-bar = 11.8085
daily_wage	overall	67.21984	31.32283	1	172	N =11597284
	between		25.67347	1	172	n = 1027186
	within		19.20074	-69.8802	209.6814	T-bar = 11.2903
lvl_of_performance	overall	2.213786	0.660556	1	4	N =11597284
	between		0.619614	1	4	n = 1027186
	within		0.287737	-0.67907	5.106643	T-bar = 11.2903
days_unemployed	overall	4.740758	50.92146	0	8400	N =11597284
	between		40.27629	0	4930.95	n = 1027186
	within		44.41046	-4602.56	5619.026	T-bar = 11.2903
industry	overall	7.409021	3.386418	1	13	N =11597284
	between		3.072174	1	13	n = 1027186
	within		1.406392	-4.16241	18.98045	T-bar = 11.2903
year	overall	1993.041	7.862785	1979	2006	N =11597284
	between		7.135941	1979	2006	n = 1027186
	within		5.605612	1972.041	2014.041	T-bar = 11.2903
vocTrain	overall	2.211839	1.035118	0	5	N =11597284
	between		1.019662	0	5	n = 1027186
	within		0.308889	-2.57077	6.656284	T-bar = 11.2903
age	overall	38.28218	11.29035	17	62	N =11597284
	between		11.41403	17	61.5	n = 1027186

Variable		Mean	Std. Dev.	Min	Max	Observations	
	within		5.605612	17.28218	59.28218	T-bar =	11.2903
ln_wage	overall	4.115953	0.550819	0	7.244428	N =	11597284
	between		0.497075	0	6.115235	n =	1027186
	within		0.326927	-0.95283	6.793103	T-bar =	11.2903
KldB2010	overall	48.9501	21.96459	11	94	N =	11597284
	between		20.83533	11	94	n =	1027186
	within		7.857297	-28.5166	126.093	T-bar =	11.2903
employment_change	overall	0.007215	0.159908	-0.92	0.77	N =	11597284
	between		0.07695	-0.92	0.77	n =	1027186
	within		0.14711	-0.96278	0.958048	T-bar =	11.2903
ln_computeruse_change	overall	0.201255	0.190787	-0.6477	0.693147	N =	11597284
(tech_age)	between		0.142315	-0.5543	0.640294	n =	1027186
	within		0.132257	-0.43904	0.846592	T-bar =	11.2903
experience	overall	6.894122	5.776531	1	28	N =	11597284
	between		3.356878	1	14.5	n =	1027186
	within		4.50226	-6.60588	20.39412	T-bar =	11.2903
ln_age	overall	3.598839	0.309569	2.833213	4.127134	N =	11597284
	between		0.31624	2.833213	4.119004	n =	1027186
	within		0.158479	2.828632	4.300951	T-bar =	11.2903
ln_lvl_of_performance	overall	0.756167	0.272669	0	1.386294	N =	11597284
	between		0.256042	0	1.386294	n =	1027186
	within		0.127371	-0.58062	2.092951	T-bar =	11.2903
ln_formerjobs	overall	0.80851	0.721245	0	4.997212	N =	11597284
	between		0.609239	0	4.468037	n =	1027186
	within		0.356096	-2.69861	3.101051	T-bar =	11.2903
ln_experience	overall	1.543743	0.936086	0	3.332205	N =	11597284
	between		0.638495	0	2.424634	n =	1027186
	within		0.750862	-0.88089	3.133166	T-bar =	11.2903
state	overall	7.10577	3.343747	1	16	N =	11597284
	between		3.453038	1	16	n =	1027186
	within		0.801492	-6.95673	21.19668	T-bar =	11.2903

Note: Where applicable, overall, between and within mean, standard deviation, minimum and maximum per variable as well as number of observations including the variable, number of persons with value for the variable and average number of observations of the variable for one person.

Table A34: *Description of the panel structure of the SIAB Data, wage data KldB2010*

```
personnumber:  1, 3, ..., 1707228                             n =    1027186
    year:  1979, 1980, ..., 2006                              T =         28
           Delta(year) = 1 unit
           Span(year)  = 28 periods
           (personnumber*year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         1       2       5        10        16      27      28
```

Freq.	Percent	Cum.	Pattern
38835	3.78	3.78	1111111111111111111111111111
32069	3.12	6.90	111111111111111
15179	1.48	8.38	1
14925	1.45	9.83	11..........................
14108	1.37	11.21	111.........................
13430	1.31	12.51	1111........................
12666	1.23	13.75	11111.......................
11962	1.16	14.91	11
11929	1.16	16.07	111111......................
862083	83.93	100.00	(other patterns)
1027186	100.00		XXXXXXXXXXXXXXXXXXXXXXXXXXXX

Table A35: *Observations per KldB2010, wage data KldB2010*

KldB2010	Freq.	Percent	Cum.
agriculture (11)	79,229	0.68	0.68
gardening (12)	117,897	1.02	1.7
raw_material_prod (21)	115,758	1	2.7
plastic_wood_process (22)	338,256	2.92	5.61
paper_process (23)	181,015	1.56	7.18
metal_making (24)	804,914	6.94	14.12
machine_car_build (25)	921,797	7.95	22.06
electrical_engineer (26)	349,097	3.01	25.07
tech_research_construction (27)	479,721	4.14	29.21
textile_process (28)	174,940	1.51	30.72
food_process (29)	337,737	2.91	33.63
architecture (31)	112,641	0.97	34.6
construction (32)	496,578	4.28	38.88
interior_constr (33)	210,972	1.82	40.7
build_engineer (34)	228,113	1.97	42.67
math_bio_chem (41)	232,487	2	44.68
geo (42)	4,617	0.04	44.72
IT (43)	145,875	1.26	45.97
logistics (51)	661,248	5.7	51.67
drivers (52)	534,778	4.61	56.29
safety (53)	150,543	1.3	57.58
cleaning_service (54)	197,932	1.71	59.29
purchasing_sales (61)	312,583	2.7	61.99
retail (62)	528,436	4.56	66.54
tourism (63)	178,445	1.54	68.08
management (71)	1,865,682	16.09	84.17
finance (72)	511,572	4.41	88.58
law (73)	66,105	0.57	89.15
medical (81)	563,710	4.86	94.01
wellness (82)	100,916	0.87	94.88
education (83)	333,288	2.87	97.75
teaching (84)	105,907	0.91	98.67
social_science (91)	26,110	0.23	98.89
marketing (92)	56,092	0.48	99.38
craftwork (93)	38,153	0.33	99.71
entertainment (94)	34,140	0.29	100
Total	11,597,284	100	

Table A36: *Observations per age, wage data KldB2010*

Age	Freq.	Percent	Cum.
17	19,319	0.17	0.17
18	54,016	0.47	0.63
19	121,324	1.05	1.68
20	190,446	1.64	3.32
21	241,674	2.08	5.4
22	276,042	2.38	7.78
23	296,637	2.56	10.34
24	309,133	2.67	13.01
25	315,919	2.72	15.73
26	321,406	2.77	18.5
27	326,079	2.81	21.32
28	329,005	2.84	24.15
29	331,395	2.86	27.01
30	331,488	2.86	29.87
31	330,346	2.85	32.72
32	329,089	2.84	35.55
33	327,122	2.82	38.37
34	323,550	2.79	41.16
35	321,760	2.77	43.94
36	319,631	2.76	46.7
37	316,910	2.73	49.43
38	315,667	2.72	52.15
39	314,662	2.71	54.86
40	313,433	2.7	57.57
41	310,711	2.68	60.24
42	307,626	2.65	62.9
43	302,990	2.61	65.51
44	297,316	2.56	68.07
45	291,182	2.51	70.58
46	283,030	2.44	73.02
47	275,028	2.37	75.4
48	268,374	2.31	77.71
49	262,215	2.26	79.97
50	255,667	2.2	82.18
51	249,626	2.15	84.33
52	243,094	2.1	86.42
53	235,722	2.03	88.46
54	227,454	1.96	90.42
55	215,515	1.86	92.28
56	195,798	1.69	93.97
57	178,733	1.54	95.51
58	158,823	1.37	96.88
59	133,704	1.15	98.03
60	109,855	0.95	98.98
61	68,296	0.59	99.56
62	50,472	0.44	100
Total	11,597,284	100	

Table A37: *Observations and levels of the "Employment Complexity" variable, wage data KldB2010*

Employment Complexity	Freq.	Percent	Cum.
1 Assistant Employment	536,890	4.63	4.63
2 Professional Employment	9,062,774	78.15	82.78
3 Complex Sepcialist Employment	979,013	8.44	91.22
4 Highly complex Expert Employment	1,018,607	8.78	100
Total	11,597,284	100	

Table A38: *Observations and levels of the "Vocational Training" variable, wage data KldB2010*

Vocational Training	Freq.	Percent	Cum.
missing	18,023	0.16	0.16
No Training	1,649,516	14.22	14.38
Vocational Training	8,300,872	71.58	85.95
Highschool	143,299	1.24	87.19
Highschool and Vocational Training	457,701	3.95	91.14
University	1,027,873	8.86	100
Total	11,597,284	100	

Table A39: *Observations per State, wage data KldB2010, wage data KldB2010*

State	Freq.	Percent	Cum.
Schleswig_Holstein	352,909	3.04	3.04
Hamburg	357,977	3.09	6.13
Niedersachsen	1,037,837	8.95	15.08
Bremen	136,660	1.18	16.26
Nordrhein_Westfalen	2,733,849	23.57	39.83
Hessen	994,779	8.58	48.41
Pheinland_Pfalz	529,750	4.57	52.98
Baden_Würtemberg	1,733,308	14.95	67.92
Bayern	1,924,221	16.59	84.51
Saarland	167,215	1.44	85.96
Berlin	464,344	4	89.96
Brandenburg	209,231	1.8	91.76
Mecklenburg_Vorpommern	147,794	1.27	93.04
Sachsen	381,481	3.29	96.33
Sachsen_Anhalt	219,624	1.89	98.22
Thüringen	206,305	1.78	100
Total	11,597,284	100	

Table A40: *Observations per W93 Industry, wage data KldB2010*

W93 Industry	Freq.	Percent	Cum.
1 (A,B,C) Agriculture, Fishing, Mining	241,809	2.09	2.09
2 (DD,DF,DG,DH) Wood manufacturing, Fuel manufacturing, Chemical manufacturing, Rubber manufacturing	556,272	4.8	6.88
3 (DJ,DK) Metal manufacturing, Machine manufacturing	1,193,184	10.29	17.17
4 (DL,DM) Office machine manufacturing, Motor vehicle manufacturing	990,409	8.54	25.71
5 (DA,DB,DC,DE,DI,DN) Food manufacturing, Textile manufacturing, Leather manufacturing, Paper manufacturing, Glass manufacturing, Furniture manufacturing	1,119,845	9.66	35.37
6 (H) Hotels and Restaurants	305,268	2.63	38
7 (F) Construction	1,100,222	9.49	47.49
8 (G) Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	1,659,396	14.31	61.79
9 (I) Transport, storage and communication	636,214	5.49	67.28
10 (J,K) Financial intermediation, real estate, renting and business activities	1,392,777	12.01	79.29
11 (E,O,P) Electricity, gas and water supply, Other community, social and personal service activities, Private households with employed persons	576,176	4.97	84.26
12 (M,N) Education, Health and social work	1,104,461	9.52	93.78
13 (L,Q) Public administration and defense; compulsory social security, Extra-territorial organizations and bodies	721,251	6.22	100
Total	11,597,284	100	

Table A41: *Observations per year of experience in occupation, wage data KldB2010*

experience	Freq.	Percent	Cum.
1	1,783,551	15.38	15.38
2	1,397,026	12.05	27.43
3	1,121,038	9.67	37.09
4	952,618	8.21	45.31
5	826,542	7.13	52.43
6	722,569	6.23	58.66
7	634,318	5.47	64.13
8	559,380	4.82	68.96
9	494,265	4.26	73.22
10	437,607	3.77	76.99
11	388,049	3.35	80.34
12	344,302	2.97	83.31
13	304,255	2.62	85.93
14	267,377	2.31	88.24
15	231,673	2	90.23
16	189,852	1.64	91.87
17	163,753	1.41	93.28
18	141,591	1.22	94.5
19	122,259	1.05	95.56
20	105,353	0.91	96.47
21	90,278	0.78	97.24
22	76,310	0.66	97.9
23	64,239	0.55	98.46
24	53,748	0.46	98.92
25	44,332	0.38	99.3
26	35,489	0.31	99.61
27	27,243	0.23	99.84
28	18,267	0.16	100
Total	11,597,284	100	

A10. *SIAB Data* in depth descriptive statistics *occupation change analysis*, *KldB2010*

Table A42: *Descriptive statistics SIAB Data, occupation change data KldB2010*

Variable		Mean	Std. Dev.	Min	Max	Observations
personnumber	overall	853999.4	493146.2	1	1707228	N = 10870916
	between		492964.4	1	1707228	n = 1041157
	within		0	853999.4	853999.4	T-bar = 10.4412
formerjobs	overall	2.917042	2.612679	1	148	N = 10870916
	between		2.159035	1	98.77778	n = 1041157
	within		1.261403	-48.64546	60.31704	T-bar = 10.4412
lvl_of_performance	overall	2.222611	0.663137	1	4	N = 10870916
	between		0.627334	1	4	n = 1041157
	within		0.275111	-0.670246	5.115468	T-bar = 10.4412
days_unemployed	overall	2.840278	40.5019	0	8766	N = 10870916
	between		42.80624	0	5113.571	n = 1041157
	within		33.8569	-4904.285	5461.174	T-bar = 10.4412
industry	overall	7.405791	3.405812	1	13	N = 10870916
	between		3.117938	1	13	n = 1041157
	within		1.319017	-4.165637	18.92579	T-bar = 10.4412
year	overall	1992.897	7.851393	1979	2006	N = 10870916
	between		7.196145	1979	2006	n = 1041157
	within		5.573682	1971.897	2013.897	T-bar = 10.4412
vocTrain	overall	2.240461	1.053063	1	5	N = 10870916
	between		1.042771	1	5	n = 1041157
	within		0.293911	-1.616681	6.097604	T-bar = 10.4412
age	overall	38.56697	11.22248	17	62	N = 10870916
	between		11.41182	17	62	n = 1041157
	within		5.573682	17.56697	59.56697	T-bar = 10.4412
KldB88	overall	49.11291	21.97109	11	94	N = 10870916
	between		20.998	11	94	n = 1041157
	within		7.415928	-29.51867	126.7493	T-bar = 10.4412

Variable		Mean	Std. Dev.	Min	Max	Observations
employ-ment_change	overall	0.0079877	0.159898	-0.92	0.77	N = 10870916
	between		0.087238	-0.92	0.77	n = 1041157
	within		0.146312	-0.997012	0.969988	T-bar = 10.4412
experience	overall	6.922468	5.752252	1	28	N = 10870916
	between		3.36693	1	25	n = 1041157
	within		4.480515	-12.62299	25.2558	T-bar = 10.4412
state	overall	7.075453	3.310043	1	16	N = 10870916
	between		3.473474	1	16	n = 1041157
	within		0.75039	-6.987047	21.16636	T-bar = 10.4412

Note: Where applicable, overall, between and within mean, standard deviation, minimum and maximum per variable as well as number of observations including the variable, number of persons with value for the variable and average number of observations of the variable for one person.

TableA43: *Description of the panel structure of the SIAB Data, occupation change data KldB2010*

```
personnumber:  1, 3, ..., 1707228                            n =    1041157
    year:  1979.0000   , 1980.0000, ..., 2006.0000          T =         28
           Delta(year) = 1 unit
           Span(year)  = 28 periods
           (personnumber*year uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         1       1       4         9        15      26      28

     Freq.  Percent    Cum.  |  Pattern
 ---------------------------+------------------------------
    26481      2.54    2.54  |  1111111111111111111111111111
    20962      2.01    4.56  |  .............111111111111111
    16276      1.56    6.12  |  ...........................1
    14523      1.39    7.51  |  11..........................
    13526      1.30    8.81  |  111.........................
    12448      1.20   10.01  |  1111........................
    11392      1.09   11.10  |  11111.......................
    10740      1.03   12.14  |  111111......................
    10682      1.03   13.16  |  ..........................11
   904127     86.84  100.00  | (other patterns)
 ---------------------------+------------------------------
  1041157    100.00          |  XXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

TableA44: *Observations per KldB2010, occupation change data KldB2010*

KldB2010	Freq.	Percent	Cum.
11	67,834	0.62	0.62
12	98,902	0.91	1.53
21	107,911	0.99	2.53
22	314,060	2.89	5.42
23	171,999	1.58	7
24	759,930	6.99	13.99
25	874,589	8.05	22.03
26	335,250	3.08	25.12
27	464,505	4.27	29.39
28	164,458	1.51	30.9
29	305,543	2.81	33.71
31	108,497	1	34.71
32	430,385	3.96	38.67
33	183,946	1.69	40.36
34	212,734	1.96	42.32
41	224,428	2.06	44.38
42	4,200	0.04	44.42
43	140,668	1.29	45.72
51	614,952	5.66	51.37
52	498,400	4.58	55.96
53	140,934	1.3	57.25
54	175,973	1.62	58.87
61	298,983	2.75	61.62
62	487,651	4.49	66.11
63	156,058	1.44	67.55
71	1,785,855	16.43	83.97
72	499,157	4.59	88.56
73	63,439	0.58	89.15
81	532,251	4.9	94.04
82	92,583	0.85	94.9
83	310,204	2.85	97.75
84	100,602	0.93	98.68
91	24,994	0.23	98.9
92	53,274	0.49	99.4
93	35,270	0.32	99.72
94	30,497	0.28	100
Total	10,870,916	100	

TableA45: *Observations per age, occupation change data KldB2010*

Age	Freq.	Percent	Cum.
17	16,948	0.16	0.16
18	43,846	0.4	0.56
19	96,652	0.89	1.45
20	155,333	1.43	2.88
21	205,516	1.89	4.77
22	241,933	2.23	6.99
23	265,605	2.44	9.44
24	280,964	2.58	12.02
25	290,674	2.67	14.69
26	298,096	2.74	17.44
27	304,241	2.8	20.24
28	308,335	2.84	23.07
29	311,557	2.87	25.94
30	312,028	2.87	28.81
31	311,749	2.87	31.68
32	310,825	2.86	34.54
33	309,150	2.84	37.38
34	305,662	2.81	40.19
35	303,692	2.79	42.98
36	302,033	2.78	45.76
37	299,575	2.76	48.52
38	298,572	2.75	51.27
39	297,786	2.74	54
40	296,350	2.73	56.73
41	294,026	2.7	59.44
42	291,685	2.68	62.12
43	287,271	2.64	64.76
44	282,352	2.6	67.36
45	276,978	2.55	69.91
46	269,309	2.48	72.38
47	261,850	2.41	74.79
48	256,283	2.36	77.15
49	250,805	2.31	79.46
50	244,933	2.25	81.71
51	239,175	2.2	83.91
52	233,661	2.15	86.06
53	227,013	2.09	88.15
54	219,388	2.02	90.17
55	207,008	1.9	92.07
56	188,108	1.73	93.8
57	171,394	1.58	95.38
58	151,630	1.39	96.77
59	128,570	1.18	97.95
60	106,771	0.98	98.94
61	66,257	0.61	99.55
62	49,327	0.45	100
Total	10,870,916	100	

Table A46: *Observations and levels of the "Employment Complexity" variable, occupation change data KldB2010*

Employment Complexity	Freq.	Percent	Cum.
1 Assistant Employment	475,984	4.38	4.38
2 Professional Employment	8,472,591	77.94	82.38
3 Complex Sepcialist Employment	948,715	8.73	91.04
4 Highly complex Expert Employment	973,626	8.96	100
Total	10,870,916	100	

Table A47: *Observations and levels of the "Vocational Training" variable, occupation change data KldB2010*

Vocational Training	Freq.	Percent	Cum.
No Training	1,531,188	14.09	14.09
Vocational Training	7,679,476	70.64	84.73
Highschool	193,995	1.78	86.51
Highschool and Vocational Training	447,542	4.12	90.63
University	1,018,715	9.37	100
Total	10,870,916	100	

Table A48: *Observations per State, occupation change data KldB2010*

State	Freq.	Percent	Cum.
Schleswig_Holstein	325,747	3	3
Hamburg	338,798	3.12	6.11
Niedersachsen	966,734	8.89	15.01
Bremen	128,251	1.18	16.19
Nordrhein_Westfalen	2,583,467	23.76	39.95
Hessen	944,269	8.69	48.64
Pheinland_Pfalz	497,572	4.58	53.21
Baden_Würtemberg	1,649,203	15.17	68.38
Bayern	1,802,036	16.58	84.96
Saarland	157,645	1.45	86.41
Berlin	431,280	3.97	90.38
Brandenburg	188,201	1.73	92.11
Mecklenburg_Vorpommern	131,265	1.21	93.32
Sachsen	344,694	3.17	96.49
Sachsen_Anhalt	196,966	1.81	98.3
Thüringen	184,788	1.7	100
Total	10,870,916	100	

Table A49: *Observations per W93 Industry, occupation change data KldB2010*

W93 Industry	Freq.	Percent	Cum.
1 (A,B,C) Agriculture, Fishing, Mining	216,483	1.99	1.99
2 (DD,DF,DG,DH) Wood manufacturing, Fuel manufacturing, Chemical manufacturing, Rubber manufacturing	533,199	4.9	6.9
3 (DJ,DK) Metal manufacturing, Machine manufacturing	1,141,499	10.5	17.4
4 (DL,DM) Office machine manufacturing, Motor vehicle manufacturing	958,240	8.81	26.21
5 (DA,DB,DC,DE,DI,DN) Food manufacturing, Textile manufacturing, Leather manufacturing, Paper manufacturing, Glass manufacturing, Furniture manufacturing	1,055,540	9.71	35.92
6 (H) Hotels and Restaurants	260,614	2.4	38.32
7 (F) Construction	980,405	9.02	47.34
8 (G) Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	1,551,230	14.27	61.61
9 (I) Transport, storage and communication	598,674	5.51	67.11
10 (J,K) Financial intermediation, real estate, renting and business activities	1,296,397	11.93	79.04
11 (E,O,P) Electricity, gas and water supply, Other community, social and personal service activities, Private households with employed persons	539,852	4.97	84.01
12 (M,N) Education, Health and social work	1,041,248	9.58	93.58
13 (L,Q) Public administration and defense; compulsory social security, Extra-territorial organizations and bodies	697,535	6.42	100
Total	10,870,916	100	

Table A50: *Observations per year of experience in occupation, occupation change data KldB2010*

Experience	Freq.	Percent	Cum.
1	1,652,376	15.2	15.2
2	1,279,922	11.77	26.97
3	1,045,399	9.62	36.59
4	895,172	8.23	44.82
5	779,772	7.17	52
6	683,518	6.29	58.29
7	601,191	5.53	63.82
8	530,799	4.88	68.7
9	469,731	4.32	73.02
10	415,971	3.83	76.85
11	368,985	3.39	80.24
12	327,136	3.01	83.25
13	288,607	2.65	85.9
14	253,180	2.33	88.23
15	218,815	2.01	90.25
16	180,635	1.66	91.91
17	155,309	1.43	93.34
18	133,927	1.23	94.57
19	115,588	1.06	95.63
20	99,348	0.91	96.55
21	84,400	0.78	97.32
22	71,054	0.65	97.98
23	59,474	0.55	98.52
24	49,330	0.45	98.98
25	40,159	0.37	99.35
26	31,852	0.29	99.64
27	23,844	0.22	99.86
28	15,422	0.14	100
Total	10,870,916	100	

A11. Wage analysis full output tables

A11.i. Regression results *overall sample* non occupation specific technological age

Table A51: *Regression (9), the impact of log technological age on log wages, overall sample, non occupation specific technological age*

Dependent variable: log wage	log technological age
	(9)
ln_techage	0.1544***
	(0.0033)
ln_age	1.3098***
	(0.0050)
lvl_of_performance	0.1426***
	(0.0018)
ln_formerjobs	0.0225***
	(0.0006)
days_unemployed	-0.0002***
	0.0000
ln_experience	0.0792***
	(0.0003)
employment_change	-0.0142***
	(0.0005)
1.vocTrain	0.0000
	(.)
2.vocTrain	0.0386***
	(0.0015)
3.vocTrain	-0.0506***
	(0.0044)
4.vocTrain	0.1229***
	(0.0028)
5.vocTrain	0.2911***
	(0.0028)
1.KldB88	0.0000
	(.)
2.KldB88	0.1700***
	(0.0042)
3.KldB88	0.1355***
	(0.0053)
4.KldB88	0.0979***
	(0.0034)
5.KldB88	0.1044***
	(0.0040)

6.KldB88	0.1758***
	(0.0052)
7.KldB88	0.1078***
	(0.0031)
8.KldB88	0.0407***
	(0.0030)
9.KldB88	0.0074*
	(0.0034)
10.KldB88	0.1260***
	(0.0032)
11.KldB88	0.0479***
	(0.0042)
12.KldB88	0.0592***
	(0.0035)
13.KldB88	0.1710***
	(0.0030)
14.KldB88	0.1293***
	(0.0038)
15.KldB88	0.0491***
	(0.0039)
16.KldB88	0.0857***
	(0.0040)
17.KldB88	0.0879***
	(0.0033)
18.KldB88	0.1446***
	(0.0034)
19.KldB88	0.0740***
	(0.0041)
20.KldB88	0.1021***
	(0.0033)
21.KldB88	0.0757***
	(0.0032)
22.KldB88	0.1705***
	(0.0041)
23.KldB88	0.0723***
	(0.0029)
24.KldB88	0.0902***
	(0.0033)
25.KldB88	0.0243***
	(0.0037)
26.KldB88	0.1098***
	(0.0057)
27.KldB88	0.1441***
	(0.0045)
28.KldB88	0.0581***
	(0.0043)
1.industry	0.0000
	(.)
2.industry	0.0799***
	(0.0030)

3.industry	0.0785***
	(0.0027)
4.industry	0.1114***
	(0.0028)
5.industry	0.0304***
	(0.0028)
6.industry	-0.2036***
	(0.0040)
7.industry	0.0188***
	(0.0027)
8.industry	-0.0223***
	(0.0027)
9.industry	-0.0385***
	(0.0029)
10.industry	-0.0520***
	(0.0027)
11.industry	-0.0063*
	(0.0031)
12.industry	-0.0179***
	(0.0031)
13.industry	0.0392***
	(0.0029)
1.state	0.0000
	(.)
2.state	0.0682***
	(0.0034)
3.state	-0.0114**
	(0.0038)
4.state	0.0279***
	(0.0051)
5.state	0.0301***
	(0.0038)
6.state	0.0618***
	(0.0040)
7.state	-0.0106*
	(0.0044)
8.state	0.0469***
	(0.0039)
9.state	0.0430***
	(0.0039)
10.state	-0.0331***
	(0.0066)
11.state	-0.0264***
	(0.0044)
12.state	-0.1509***
	(0.0047)
13.state	-0.1880***
	(0.0054)
14.state	-0.1896***
	(0.0046)

15.state	-0.1887***
	(0.0048)
16.state	-0.1918***
	(0.0050)
1979.year	0.0000
	(.)
1980.year	-0.0129***
	(0.0005)
1981.year	-0.0186***
	(0.0007)
1982.year	-0.0401***
	(0.0008)
1983.year	-0.0613***
	(0.0009)
1984.year	-0.0596***
	(0.0010)
1985.year	-0.0629***
	(0.0011)
1986.year	-0.0683***
	(0.0012)
1987.year	-0.0759***
	(0.0013)
1988.year	-0.0902***
	(0.0014)
1989.year	-0.0917***
	(0.0016)
1990.year	-0.0706***
	(0.0017)
1991.year	-0.0451***
	(0.0018)
1992.year	-0.0399***
	(0.0019)
1993.year	-0.0392***
	(0.0020)
1994.year	-0.0545***
	(0.0022)
1995.year	-0.0619***
	(0.0023)
1996.year	-0.0849***
	(0.0024)
1997.year	-0.1160***
	(0.0026)
1998.year	-0.1476***
	(0.0027)
1999.year	-0.1632***
	(0.0028)
2000.year	-0.1839***
	(0.0030)
2001.year	-0.1972***
	(0.0031)

2002.year	-0.2193***
	(0.0033)
2003.year	-0.2495***
	(0.0034)
2004.year	-0.2836***
	(0.0036)
2005.year	-0.3165***
	(0.0037)
2006.year	-0.3451***
	(0.0039)
Constant	-0.9108***
	(0.0168)
N	11,012,285
R-sq	0.5166

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level. ln_techage is not interacted with occupation dummies.*

A11.ii. Regression results *overall sample* - full output table

Table A52: *Regression (1), the impact of log technological age on log wages, overall sample, full output table*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)
ln_agriculture_fishing (1)	-0.2747***
	(0.0113)
ln_miners_stone_workers (2)	-0.4973***
	(0.0172)
ln_ceramic_glas (3)	-0.3295***
	(0.0221)
ln_chemistry_synthetic_workers (4)	-0.1028***
	(0.0070)
ln_paper_print (5)	-0.0943***
	(0.0104)
ln_woodworking (6)	-0.1033
	(0.0920)
ln_metal_works (7)	-0.0850***
	(0.0055)
ln_mechanics (8)	-0.0810***
	(0.0047)
ln_electricians (9)	0.0452***
	(0.0067)
ln_assembly (10)	-0.1107***
	(0.0078)
ln_textile_clothing_leather_fur (11)	-0.4416***
	(0.0213)
ln_food (12)	-0.4447***
	(0.0133)
ln_construction (13)	-0.7668***
	(0.0122)
ln_interior_construction (14)	-0.4682***
	(0.0147)
ln_carpenter (15)	-0.4003***
	(0.0119)
ln_painter (16)	-0.3426***
	(0.0123)
ln_product_testing (17)	-0.0773***
	(0.0087)
ln_machinist (18)	-0.0528***
	(0.0090)
ln_engineer_math_chem (19)	0.3367***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample*
	(1)
	(0.0090)
ln_technical_specilaist (20)	0.3143***
	(0.0054)
ln_goods_merchants (21)	0.0389***
	(0.0071)
ln_service_merchants (22)	0.3714***
	(0.0075)
ln_traffic (23)	-0.3411***
	(0.0060)
ln_administration (24)	0.1746***
	(0.0043)
ln_regulatory_safety (25)	-0.0975***
	(0.0097)
ln_writing_art (26)	0.1741***
	(0.0144)
ln_healthcare (27)	-0.1575***
	(0.0070)
ln_social_education_science (28)	0.1381***
	(0.0079)
ln_age	1.3427***
	(0.0050)
lvl_of_performance	0.1351***
	(0.0018)
ln_formerjobs	0.0233***
	(0.0006)
days_unemployed	-0.0002***
	0.0000
ln_experience	0.0809***
	(0.0003)
employment_change	0.0014**
	(0.0005)
1.vocTrain	0.0000
	(.)
2.vocTrain	0.0510***
	(0.0015)
3.vocTrain	-0.0407***
	(0.0044)
4.vocTrain	0.1214***
	(0.0027)
5.vocTrain	0.2732***
	(0.0028)
1.KldB88	0.0000
	(.)
2.KldB88	0.1694***
	(0.0044)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample*
	(1)
3.KldB88	0.1328***
	(0.0056)
4.KldB88	0.1097***
	(0.0037)
5.KldB88	0.1230***
	(0.0046)
6.KldB88	0.1288***
	(0.0054)
7.KldB88	0.0949***
	(0.0033)
8.KldB88	0.0360***
	(0.0032)
9.KldB88	0.0046
	(0.0037)
10.KldB88	0.1132***
	(0.0034)
11.KldB88	0.0318***
	(0.0044)
12.KldB88	0.0458***
	(0.0037)
13.KldB88	0.1560***
	(0.0032)
14.KldB88	0.1359***
	(0.0041)
15.KldB88	0.0577***
	(0.0042)
16.KldB88	0.0745***
	(0.0042)
17.KldB88	0.0893***
	(0.0036)
18.KldB88	0.1337***
	(0.0038)
19.KldB88	-0.0373***
	(0.0056)
20.KldB88	0.0088*
	(0.0039)
21.KldB88	0.0634***
	(0.0036)
22.KldB88	0.0558***
	(0.0051)
23.KldB88	0.0916***
	(0.0031)
24.KldB88	0.0447***
	(0.0037)
25.KldB88	0.0688***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)
	(0.0047)
26.KldB88	0.0737***
	(0.0071)
27.KldB88	0.1845***
	(0.0049)
28.KldB88	0.0288***
	(0.0049)
1.industry	0.0000
	(.)
2.industry	0.0832***
	(0.0030)
3.industry	0.0815***
	(0.0027)
4.industry	0.1156***
	(0.0028)
5.industry	0.0328***
	(0.0027)
6.industry	-0.2013***
	(0.0040)
7.industry	0.0178***
	(0.0027)
8.industry	-0.0188***
	(0.0027)
9.industry	-0.0306***
	(0.0029)
10.industry	-0.0496***
	(0.0027)
11.industry	(0.0040)
	(0.0031)
12.industry	-0.0144***
	(0.0031)
13.industry	0.0432***
	(0.0029)
1.state	0.0000
	(.)
2.state	0.0670***
	(0.0033)
3.state	-0.0107**
	(0.0037)
4.state	0.0292***
	(0.0051)
5.state	0.0299***
	(0.0037)
6.state	0.0607***
	(0.0039)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample*
	(1)
7.state	-0.0103*
	(0.0043)
8.state	0.0468***
	(0.0039)
9.state	0.0422***
	(0.0039)
10.state	-0.0315***
	(0.0066)
11.state	-0.0289***
	(0.0043)
12.state	-0.1534***
	(0.0046)
13.state	-0.1906***
	(0.0054)
14.state	-0.1928***
	(0.0045)
15.state	-0.1909***
	(0.0047)
16.state	-0.1931***
	(0.0050)
1979.year	0.0000
	(.)
1980.year	-0.0158***
	(0.0005)
1981.year	-0.0231***
	(0.0007)
1982.year	-0.0454***
	(0.0008)
1983.year	-0.0677***
	(0.0009)
1984.year	-0.0657***
	(0.0010)
1985.year	-0.0709***
	(0.0011)
1986.year	-0.0790***
	(0.0012)
1987.year	-0.0851***
	(0.0013)
1988.year	-0.0991***
	(0.0014)
1989.year	-0.1003***
	(0.0015)
1990.year	-0.0789***
	(0.0017)
1991.year	-0.0543***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample*
	(1)
	(0.0018)
1992.year	-0.0500***
	(0.0019)
1993.year	-0.0468***
	(0.0020)
1994.year	-0.0614***
	(0.0021)
1995.year	-0.0675***
	(0.0023)
1996.year	-0.0904***
	(0.0024)
1997.year	-0.1203***
	(0.0025)
1998.year	-0.1513***
	(0.0027)
1999.year	-0.1653***
	(0.0028)
2000.year	-0.1786***
	(0.0030)
2001.year	-0.1851***
	(0.0031)
2002.year	-0.2003***
	(0.0032)
2003.year	-0.2230***
	(0.0034)
2004.year	-0.2509***
	(0.0035)
2005.year	-0.2782***
	(0.0037)
2006.year	-0.3012***
	(0.0038)
Constant	-1.0005***
	(0.0167)
N	11,012,285
R-sq	0.5218

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level*

A11.iii. Regression results *subsample 79, subsample 90* and *subsample 00* - full output tables

Table A53: *Regressions (1), (2), (3) and (4), the impact of log technological age on log wages, overall sample, subsample 79, subsample 90 and subsample 00, full output table*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific co-efficients of log tech age *subsample 79* (2)	Occupation specific coefficients of log tech age *subsample 90* (3)	Occupation specific coefficients of log tech age *subsample 00* (4)
ln_agriculture_fishing (1)	-0.2747***	-0.1796	0.2614***	-0.4193***
	(0.0113)	(0.1630)	(0.0429)	(0.0180)
ln_miners_stone_workers (2)	-0.4973***	-0.5950***	-0.3586	-0.2791***
	(0.0172)	(0.1669)	(0.2079)	(0.0251)
ln_ceramic_glas (3)	-0.3295***	-0.0886	-0.0906*	-0.4717***
	(0.0221)	(0.2955)	(0.0428)	(0.0516)
ln_chemistry_synthetic_workers (4)	-0.1028***	0.4270***	0.0499*	-0.2104***
	(0.0070)	(0.0325)	(0.0223)	(0.0135)
ln_paper_print (5)	-0.0943***	0.3009***	0.0874*	-0.3841***
	(0.0104)	(0.0336)	(0.0406)	(0.0216)
ln_woodworking (6)	-0.1033	-0.7614**	-0.0958	-0.1971
	(0.0920)	(0.2592)	(0.1444)	(0.1475)
ln_metal_works (7)	-0.0850***	0.0633	-0.3130***	-0.1330***
	(0.0055)	(0.0583)	(0.0580)	(0.0078)
ln_mechanics (8)	-0.0810***	0.3213***	0.1729***	-0.2240***
	(0.0047)	(0.0362)	(0.0206)	(0.0078)
ln_electricians (9)	0.0452***	0.3947***	0.2364***	-0.2067***
	(0.0067)	(0.0246)	(0.0197)	(0.0155)
ln_assembly (10)	-0.1107***	-0.2699***	-0.0071	-0.2210***
	(0.0078)	(0.0620)	(0.0454)	(0.0114)
ln_textile_clothing_leather_fur (11)	-0.4416***	-1.0598***	-0.1720*	-0.4072***
	(0.0213)	(0.1501)	(0.0793)	(0.0266)
ln_food (12)	-0.4447***	-0.7943***	0.1564*	-0.5231***
	(0.0133)	(0.1199)	(0.0642)	(0.0204)
ln_construction (13)	-0.7668***	-1.0211***	-0.2442***	-0.6716***
	(0.0122)	(0.1085)	(0.0570)	(0.0204)
ln_interior_construction (14)	-0.4682***	-0.6219***	-0.0829	-0.5075***
	(0.0147)	(0.1347)	(0.0672)	(0.0222)
ln_carpenter (15)	-0.4003***	-0.0738	0.0121	-0.5193***
	(0.0119)	(0.1012)	(0.0444)	(0.0194)
ln_painter (16)	-0.3426***	-0.1234	0.2359*	-0.3610***
	(0.0123)	(0.1441)	(0.0984)	(0.0196)
ln_product_testing (17)	-0.0773***	0.1956***	0.1794***	-0.2417***
	(0.0087)	(0.0349)	(0.0369)	(0.0175)
ln_machinist (18)	-0.0528***	0.3608***	0.3222***	-0.1435***
	(0.0090)	(0.0636)	(0.0539)	(0.0135)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample*	Occupation specific coefficients of log tech age *subsample 79*	Occupation specific coefficients of log tech age *subsample 90*	Occupation specific coefficients of log tech age *subsample 00*
	(1)	(2)	(3)	(4)
ln_engineer_math_chem (19)	0.3367***	0.5615***	0.8318***	-0.1514***
	(0.0090)	(0.0170)	(0.0236)	(0.0370)
ln_technical_specilaist (20)	0.3143***	0.7065***	0.5092***	-0.1634***
	(0.0054)	(0.0120)	(0.0139)	(0.0255)
ln_goods_merchants (21)	0.0389***	0.4009***	0.4187***	-0.3603***
	(0.0071)	(0.0223)	(0.0167)	(0.0163)
ln_service_merchants (22)	0.3714***	0.5586***	0.7636***	-0.2162***
	(0.0075)	(0.0112)	(0.0220)	(0.0310)
ln_traffic (23)	-0.3411***	-0.2268***	0.1018***	-0.4014***
	(0.0060)	(0.0418)	(0.0273)	(0.0107)
ln_administration (24)	0.1746***	0.3492***	0.6224***	-0.1918***
	(0.0043)	(0.0078)	(0.0130)	(0.0216)
ln_regulatory_safety (25)	-0.0975***	0.2721***	0.2573***	-0.3206***
	(0.0097)	(0.0301)	(0.0200)	(0.0376)
ln_writing_art (26)	0.1741***	0.4520***	0.5039***	-0.2203***
	(0.0144)	(0.0349)	(0.0344)	(0.0511)
ln_healthcare (27)	-0.1575***	-0.0034	0.1975***	-0.3905***
	(0.0070)	(0.0304)	(0.0119)	(0.0221)
ln_social_education_science (28)	0.1381***	0.5532***	0.5002***	-0.1896***
	(0.0079)	(0.0399)	(0.0167)	(0.0214)
ln_age	1.3427***	1.7909***	1.2280***	1.3784***
	(0.0050)	(0.0082)	(0.0089)	(0.0155)
lvl_of_performance	0.1351***	0.0823***	0.0863***	0.0969***
	(0.0018)	(0.0029)	(0.0024)	(0.0039)
ln_formerjobs	0.0233***	0.0509***	0.0410***	0.0085***
	(0.0006)	(0.0010)	(0.0008)	(0.0014)
days_unemployed	-0.0002***	0.0001	-0.0002***	-0.0001***
	0.0000	(0.0001)	0.0000	0.0000
ln_experience	0.0809***	0.0652***	0.0600***	0.0364***
	(0.0003)	(0.0006)	(0.0004)	(0.0006)
employment_change	0.0014**	-0.0074***	0.0051***	0.0071***
	(0.0005)	(0.0008)	(0.0006)	(0.0012)
1.vocTrain	0	0	0	0
	(.)	(.)	(.)	(.)
2.vocTrain	0.0510***	0.0351***	0.0414***	0.1723***
	(0.0015)	(0.0020)	(0.0025)	(0.0054)
3.vocTrain	-0.0407***	-0.0112	-0.0358***	0.0076
	(0.0044)	(0.0067)	(0.0068)	(0.0118)
4.vocTrain	0.1214***	0.0936***	0.0907***	0.2267***
	(0.0027)	(0.0050)	(0.0040)	(0.0072)
5.vocTrain	0.2732***	0.2203***	0.1941***	0.3366***
	(0.0028)	(0.0053)	(0.0042)	(0.0077)
1.KldB88	0	0	0	0
	(.)	(.)	(.)	(.)

Dependent variable: log daily wage	Occupation specific coeffi-cients of log tech age *overall sample* (1)	Occupation specific co-efficients of log tech age *subsample 79* (2)	Occupation specific coeffi-cients of log tech age *subsample 90* (3)	Occupation specific coeffi-cients of log tech age *subsample 00* (4)
2.KldB88	0.1694***	0.1684***	0.1532***	0.0494***
	(0.0044)	(0.0067)	(0.0099)	(0.0131)
3.KldB88	0.1328***	0.1341***	0.1260***	0.1263***
	(0.0056)	(0.0082)	(0.0085)	(0.0203)
4.KldB88	0.1097***	0.1021***	0.1035***	0.0855***
	(0.0037)	(0.0060)	(0.0063)	(0.0106)
5.KldB88	0.1230***	0.0982***	0.1012***	0.1458***
	(0.0046)	(0.0071)	(0.0103)	(0.0141)
6.KldB88	0.1288***	0.1304***	0.1226***	-0.0083
	(0.0054)	(0.0083)	(0.0080)	(0.0163)
7.KldB88	0.0949***	0.1250***	0.1284***	0.0285**
	(0.0033)	(0.0055)	(0.0060)	(0.0091)
8.KldB88	0.0360***	0.0608***	0.0388***	0.0038
	(0.0032)	(0.0054)	(0.0051)	(0.0084)
9.KldB88	0.0046	0.0350***	-0.011	0.0115
	(0.0037)	(0.0061)	(0.0066)	(0.0104)
10.KldB88	0.1132***	0.1309***	0.1131***	0.0591***
	(0.0034)	(0.0058)	(0.0055)	(0.0093)
11.KldB88	0.0318***	0.0432***	0.0216**	-0.0209
	(0.0044)	(0.0066)	(0.0068)	(0.0129)
12.KldB88	0.0458***	0.0514***	0.0452***	-0.0022
	(0.0037)	(0.0061)	(0.0058)	(0.0101)
13.KldB88	0.1560***	0.1371***	0.1497***	0.0796***
	(0.0032)	(0.0056)	(0.0049)	(0.0087)
14.KldB88	0.1359***	0.1336***	0.1202***	0.1019***
	(0.0041)	(0.0067)	(0.0070)	(0.0107)
15.KldB88	0.0577***	0.0610***	0.0627***	0.0397***
	(0.0042)	(0.0069)	(0.0069)	(0.0117)
16.KldB88	0.0745***	0.0852***	0.0925***	0.0201
	(0.0042)	(0.0069)	(0.0072)	(0.0111)
17.KldB88	0.0893***	0.1021***	0.0650***	0.0360***
	(0.0036)	(0.0057)	(0.0073)	(0.0109)
18.KldB88	0.1337***	0.1343***	0.1154***	0.0510***
	(0.0038)	(0.0063)	(0.0073)	(0.0104)
19.KldB88	-0.0373***	-0.0236**	-0.3080***	0.0717***
	(0.0056)	(0.0086)	(0.0128)	(0.0212)
20.KldB88	0.0088*	0.0037	-0.0817***	0.0907***
	(0.0039)	(0.0063)	(0.0073)	(0.0155)
21.KldB88	0.0634***	0.0385***	-0.0119*	0.0865***
	(0.0036)	(0.0058)	(0.0057)	(0.0099)
22.KldB88	0.0558***	0.004	-0.2026***	0.1777***
	(0.0051)	(0.0076)	(0.0119)	(0.0173)
23.KldB88	0.0916***	0.1069***	0.0668***	0.0183*
	(0.0031)	(0.0053)	(0.0050)	(0.0083)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age *subsample 79* (2)	Occupation specific coefficients of log tech age *subsample 90* (3)	Occupation specific coefficients of log tech age *subsample 00* (4)
24.KldB88	0.0447***	0.0297***	-0.1776***	0.0952***
	(0.0037)	(0.0060)	(0.0075)	(0.0136)
25.KldB88	0.0688***	0.0439***	-0.0107	0.0886***
	(0.0047)	(0.0072)	(0.0083)	(0.0207)
26.KldB88	0.0737***	0.0874***	-0.0445**	0.0911***
	(0.0071)	(0.0101)	(0.0137)	(0.0252)
27.KldB88	0.1845***	0.1390***	0.0730***	0.1807***
	(0.0049)	(0.0081)	(0.0071)	(0.0142)
28.KldB88	0.0288***	0.0427***	-0.0256***	0.0143
	(0.0049)	(0.0087)	(0.0074)	(0.0136)
1.industry	0	0	0	0
	(.)	(.)	(.)	(.)
2.industry	0.0832***	0.0548***	0.0625***	0.1025***
	(0.0030)	(0.0051)	(0.0040)	(0.0062)
3.industry	0.0815***	0.0573***	0.0629***	0.1169***
	(0.0027)	(0.0047)	(0.0036)	(0.0058)
4.industry	0.1156***	0.0851***	0.0819***	0.1337***
	(0.0028)	(0.0049)	(0.0038)	(0.0059)
5.industry	0.0328***	0.0082	0.0246***	0.0707***
	(0.0027)	(0.0047)	(0.0037)	(0.0059)
6.industry	-0.2013***	-0.1919***	-0.1878***	-0.1511***
	(0.0040)	(0.0066)	(0.0055)	(0.0088)
7.industry	0.0178***	0.0033	0.0290***	0.0605***
	(0.0027)	(0.0047)	(0.0035)	(0.0056)
8.industry	-0.0188***	-0.0478***	-0.0141***	0.0352***
	(0.0027)	(0.0047)	(0.0035)	(0.0055)
9.industry	-0.0306***	-0.0398***	-0.0220***	0.005
	(0.0029)	(0.0051)	(0.0038)	(0.0059)
10.industry	-0.0496***	-0.0419***	-0.0601***	-0.0530***
	(0.0027)	(0.0049)	(0.0036)	(0.0055)
11.industry	-0.004	-0.0323***	-0.0067	-0.008
	(0.0031)	(0.0056)	(0.0040)	(0.0063)
12.industry	-0.0144***	-0.0354***	-0.0105**	-0.0298***
	(0.0031)	(0.0056)	(0.0040)	(0.0063)
13.industry	0.0432***	-0.0170***	0.0322***	0.0463***
	(0.0029)	(0.0049)	(0.0038)	(0.0067)
1.state	0	0	0	0
	(.)	(.)	(.)	(.)
2.state	0.0670***	0.0597***	0.0478***	0.0191**
	(0.0033)	(0.0051)	(0.0048)	(0.0065)
3.state	-0.0107**	-0.0132*	-0.0026	-0.0181**
	(0.0037)	(0.0060)	(0.0052)	(0.0069)
4.state	0.0292***	0.0268***	0.0287***	0.011
	(0.0051)	(0.0079)	(0.0073)	(0.0099)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific co-efficients of log tech age *subsample 79* (2)	Occupation specific coefficients of log tech age *subsample 90* (3)	Occupation specific coefficients of log tech age *subsample 00* (4)
5.state	0.0299***	0.0149*	0.0296***	0.006
	(0.0037)	(0.0060)	(0.0053)	(0.0069)
6.state	0.0607***	0.0365***	0.0465***	0.0331***
	(0.0039)	(0.0064)	(0.0056)	(0.0073)
7.state	-0.0103*	-0.0211**	0.0027	-0.0185*
	(0.0043)	(0.0070)	(0.0062)	(0.0081)
8.state	0.0468***	0.0167**	0.0450***	0.0288***
	(0.0039)	(0.0063)	(0.0056)	(0.0072)
9.state	0.0422***	0.003	0.0351***	0.0269***
	(0.0039)	(0.0064)	(0.0056)	(0.0071)
10.state	-0.0315***	-0.0424***	-0.0258**	-0.0502***
	(0.0066)	(0.0102)	(0.0099)	(0.0120)
11.state	-0.0289***	0.0127	-0.0581***	-0.0962***
	(0.0043)	(0.0079)	(0.0060)	(0.0079)
12.state	-0.1534***		-0.1614***	-0.1639***
	(0.0046)		(0.0061)	(0.0080)
13.state	-0.1906***		-0.1937***	-0.1753***
	(0.0054)		(0.0068)	(0.0088)
14.state	-0.1928***		-0.1887***	-0.1943***
	(0.0045)		(0.0061)	(0.0080)
15.state	-0.1909***		-0.1855***	-0.1879***
	(0.0047)		(0.0063)	(0.0082)
16.state	-0.1931***		-0.1986***	-0.1783***
	(0.0050)		(0.0066)	(0.0084)
1979.year	0	0		
	(.)	(.)		
1980.year	-0.0158***	-0.0225***		
	(0.0005)	(0.0006)		
1981.year	-0.0231***	-0.0403***		
	(0.0007)	(0.0009)		
1982.year	-0.0454***	-0.0744***		
	(0.0008)	(0.0011)		
1983.year	-0.0677***	-0.1086***		
	(0.0009)	(0.0014)		
1984.year	-0.0657***	-0.1193***		
	(0.0010)	(0.0016)		
1985.year	-0.0709***	-0.1366***		
	(0.0011)	(0.0018)		
1986.year	-0.0790***	-0.1562***		
	(0.0012)	(0.0020)		
1987.year	-0.0851***	-0.1758***		
	(0.0013)	(0.0023)		
1988.year	-0.0991***	-0.2024***		
	(0.0014)	(0.0026)		

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample*	Occupation specific coefficients of log tech age *subsample 79*	Occupation specific coefficients of log tech age *subsample 90*	Occupation specific coefficients of log tech age *subsample 00*
	(1)	(2)	(3)	(4)
1989.year	-0.1003***	-0.2157***		
	(0.0015)	(0.0029)		
1990.year	-0.0789***		0	
	(0.0017)		(.)	
1991.year	-0.0543***		0.0226***	
	(0.0018)		(0.0005)	
1992.year	-0.0500***		0.0241***	
	(0.0019)		(0.0008)	
1993.year	-0.0468***		0.0272***	
	(0.0020)		(0.0011)	
1994.year	-0.0614***		0.0118***	
	(0.0021)		(0.0014)	
1995.year	-0.0675***		0.0055**	
	(0.0023)		(0.0017)	
1996.year	-0.0904***		-0.0172***	
	(0.0024)		(0.0020)	
1997.year	-0.1203***		-0.0456***	
	(0.0025)		(0.0023)	
1998.year	-0.1513***		-0.0744***	
	(0.0027)		(0.0026)	
1999.year	-0.1653***		-0.0881***	
	(0.0028)		(0.0030)	
2000.year	-0.1786***			0
	(0.0030)			(.)
2001.year	-0.1851***			-0.001
	(0.0031)			(0.0006)
2002.year	-0.2003***			-0.0088***
	(0.0032)			(0.0010)
2003.year	-0.2230***			-0.0237***
	(0.0034)			(0.0014)
2004.year	-0.2509***			-0.0434***
	(0.0035)			(0.0018)
2005.year	-0.2782***			-0.0616***
	(0.0037)			(0.0023)
2006.year	-0.3012***			-0.0743***
	(0.0038)			(0.0027)
Constant	-1.0005***	-2.6854***	-0.5272***	-0.9607***
	(0.0167)	(0.0288)	(0.0314)	(0.0560)
N	11,012,285	3,830,276	4,360,117	2,821,892
R-sq	0.5218	0.3935	0.2648	0.1033

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A12. Internet usage graph

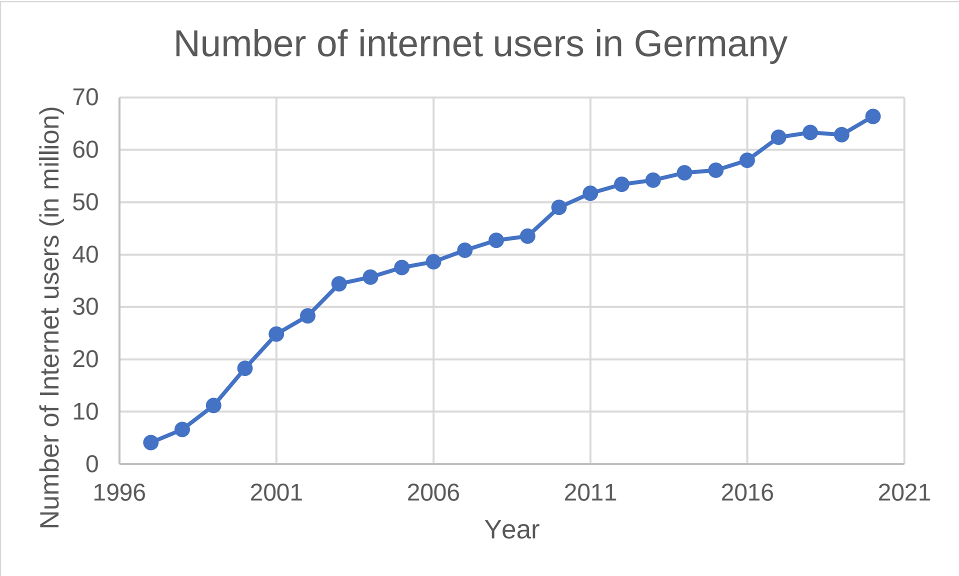

Figure A7: *Number of internet users in Germany*

Note: *Number of internet users in Germany* according to *ARD/ZDF-Onlinestudie 2020* (2020). Observations are 14 years and older who used the internet at least occasionally.

A13. Robustness checks wage analysis full output tables

A13.i. Regression *overall sample* using *KldB2010* - full output table

Table A54: *Regression (10), the impact of log technological age on log wages, overall sample, KldB2010, full output table*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)
ln_agriculture (11)	-0.2006***
	(0.0158)
ln_gardening (12)	-0.3060***
	(0.0187)
ln_raw_material_prod (21)	-0.4640***
	(0.0140)
ln_plastic_wood_process (22)	-0.2758***
	(0.0068)
ln_paper_process (23)	-0.0521***
	(0.0092)
ln_metal_making (24)	-0.1111***
	(0.0046)
ln_machine_car_build (25)	0.0769***
	(0.0044)
ln_electrical_engineer (26)	0.3022***
	(0.0080)
ln_tech_research_construction (27)	0.2605***
	(0.0056)
ln_textile_process (28)	-0.4062***
	(0.0186)
ln_food_process (29)	-0.4124***
	(0.0129)
ln_architecture (31)	0.2186***
	(0.0116)
ln_construction (32)	-0.7567***
	(0.0131)
ln_interior_constr (33)	-0.5126***
	(0.0126)
ln_build_engineer (34)	-0.1721***
	(0.0092)
ln_math_bio_chem (41)	0.1621***
	(0.0078)
ln_geo (42)	-0.1644***
	(0.0382)
ln_IT (43)	0.5008***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)
	(0.0134)
ln_logistics (51)	-0.1368***
	(0.0059)
ln_drivers (52)	-0.5455***
	(0.0100)
ln_safety (53)	-0.0848***
	(0.0101)
ln_cleaning_service (54)	-0.5152***
	(0.0450)
ln_purchasing_sales (61)	0.2612***
	(0.0074)
ln_retail (62)	-0.1683***
	(0.0087)
ln_tourism (63)	-0.4832***
	(0.0184)
ln_management (71)	0.1255***
	(0.0041)
ln_finance (72)	0.3978***
	(0.0074)
ln_law (73)	0.2398***
	(0.0172)
ln_medical (81)	-0.1445***
	(0.0069)
ln_wellness (82)	-0.5366***
	(0.0265)
ln_education (83)	0.0592***
	(0.0076)
ln_teaching (84)	0.1993***
	(0.0115)
ln_social_science (91)	0.3833***
	(0.0297)
ln_marketing (92)	0.3245***
	(0.0191)
ln_craftwork (93)	-0.1948***
	(0.0217)
ln_entertainment (94)	0.0467
	(0.0328)
ln_age	1.3144***
	(0.0049)
lvl_of_performance	0.1215***
	(0.0016)
ln_formerjobs	0.0267***
	(0.0006)
days_unemployed	-0.0002***
	0.0000
ln_experience	0.0798***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)
	(0.0003)
0.vocTrain	0
	(.)
1.vocTrain	-0.0564***
	(0.0164)
2.vocTrain	-0.0099
	(0.0163)
3.vocTrain	-0.0948***
	(0.0168)
4.vocTrain	0.0661***
	(0.0165)
5.vocTrain	0.2235***
	(0.0165)
11.KldB2010	0
	(.)
12.KldB2010	-0.0001
	(0.0053)
21.KldB2010	0.1606***
	(0.0053)
22.KldB2010	0.0900***
	(0.0049)
23.KldB2010	0.1142***
	(0.0057)
24.KldB2010	0.0740***
	(0.0047)
25.KldB2010	0.0432***
	(0.0048)
26.KldB2010	0.0353***
	(0.0054)
27.KldB2010	0.0403***
	(0.0053)
28.KldB2010	0.0419***
	(0.0055)
29.KldB2010	0.0340***
	(0.0051)
31.KldB2010	0.0479***
	(0.0077)
32.KldB2010	0.1509***
	(0.0048)
33.KldB2010	0.1172***
	(0.0051)
34.KldB2010	0.0797***
	(0.0051)
41.KldB2010	0.0616***
	(0.0057)
42.KldB2010	0.3550***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)
	(0.0324)
43.KldB2010	-0.0557***
	(0.0083)
51.KldB2010	0.0887***
	(0.0048)
52.KldB2010	0.0714***
	(0.0048)
53.KldB2010	0.0644***
	(0.0062)
54.KldB2010	-0.0169**
	(0.0052)
61.KldB2010	0.0798***
	(0.0056)
62.KldB2010	0.0358***
	(0.0050)
63.KldB2010	0.0689***
	(0.0060)
71.KldB2010	0.0758***
	(0.0050)
72.KldB2010	0.0527***
	(0.0062)
73.KldB2010	0.0848***
	(0.0095)
81.KldB2010	0.1747***
	(0.0060)
82.KldB2010	-0.1600***
	(0.0087)
83.KldB2010	0.0343***
	(0.0057)
84.KldB2010	0.0093
	(0.0073)
91.KldB2010	-0.0117
	(0.0138)
92.KldB2010	0.0365***
	(0.0106)
93.KldB2010	0.0732***
	(0.0080)
94.KldB2010	0.1641***
	(0.0127)
1.industry	0
	(.)
2.industry	0.0926***
	(0.0029)
3.industry	0.0886***
	(0.0027)
4.industry	0.1232***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010)* *overall sample* (10)
	(0.0028)
5.industry	0.0378***
	(0.0027)
6.industry	-0.1898***
	(0.0035)
7.industry	0.0173***
	(0.0027)
8.industry	-0.0117***
	(0.0026)
9.industry	-0.0163***
	(0.0029)
10.industry	-0.0516***
	(0.0027)
11.industry	-0.0163***
	(0.0030)
12.industry	0.0042
	(0.0030)
13.industry	0.0477***
	(0.0028)
1.state	0
	(.)
2.state	0.0692***
	(0.0033)
3.state	-0.0100**
	(0.0036)
4.state	0.0279***
	(0.0049)
5.state	0.0285***
	(0.0036)
6.state	0.0606***
	(0.0038)
7.state	-0.0123**
	(0.0042)
8.state	0.0454***
	(0.0038)
9.state	0.0426***
	(0.0038)
10.state	-0.0324***
	(0.0064)
11.state	-0.0276***
	(0.0042)
12.state	-0.1526***
	(0.0045)
13.state	-0.1857***
	(0.0052)
14.state	-0.1931***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)
	(0.0044)
15.state	-0.1928***
	(0.0047)
16.state	-0.1931***
	(0.0049)
1979.year	0
	(.)
1980.year	-0.0147***
	(0.0005)
1981.year	-0.0199***
	(0.0007)
1982.year	-0.0411***
	(0.0008)
1983.year	-0.0626***
	(0.0009)
1984.year	-0.0600***
	(0.0010)
1985.year	-0.0647***
	(0.0011)
1986.year	-0.0715***
	(0.0012)
1987.year	-0.0764***
	(0.0013)
1988.year	-0.0899***
	(0.0014)
1989.year	-0.0902***
	(0.0015)
1990.year	-0.0679***
	(0.0016)
1991.year	-0.0424***
	(0.0018)
1992.year	-0.0369***
	(0.0019)
1993.year	-0.0327***
	(0.0020)
1994.year	-0.0467***
	(0.0021)
1995.year	-0.0517***
	(0.0023)
1996.year	-0.0746***
	(0.0024)
1997.year	-0.1038***
	(0.0025)
1998.year	-0.1343***
	(0.0026)
1999.year	-0.1477***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010)* *overall sample* (10)
	(0.0028)
2000.year	-0.1607***
	(0.0029)
2001.year	-0.1668***
	(0.0031)
2002.year	-0.1814***
	(0.0032)
2003.year	-0.2042***
	(0.0034)
2004.year	-0.2324***
	(0.0035)
2005.year	-0.2591***
	(0.0036)
2006.year	-0.2816***
	(0.0038)
employment_change	0.0068***
	(0.0005)
_cons	-0.8612***
	(0.0233)
N	11,597,284
R-sq	0.5145

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A13.ii. Regressions subsample 79, subsample 90 and subsample 00 using KldB2010 - full output table

Table A55: *Regressions (10), (11), (12) and (13), the impact of log technological age on log wages, overall sample, subsample 79, subsample 90 and subsample 00, KldB2010, full output table*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010)* *subsample 79* (11)	Occupation specific coefficients of log tech age *(KldB2010)* *subsample 90* (12)	Occupation specific coefficients of log tech age *(KldB2010)* *subsample 00* (13)
ln_agriculture (11)	-0.2006***	-0.3113	0.3369***	-0.2918***
	(0.0158)	(0.1913)	(0.0895)	(0.0208)
ln_gardening (12)	-0.3060***	0.4745*	0.4238***	-0.4501***
	(0.0187)	(0.2119)	(0.0863)	(0.0264)
ln_raw_material_prod (21)	-0.4640***	-0.7263***	-0.4257***	-0.2948***
	(0.0140)	(0.0938)	(0.0832)	(0.0217)
ln_plastic_wood_process (22)	-0.2758***	-0.0831	-0.1110**	-0.3046***
	(0.0068)	(0.0523)	(0.0348)	(0.0101)
ln_paper_process (23)	-0.0521***	0.2844***	0.0868**	-0.3545***
	(0.0092)	(0.0279)	(0.0268)	(0.0241)
ln_metal_making (24)	-0.1111***	0.0426	-0.1058***	-0.1646***
	(0.0046)	(0.0377)	(0.0287)	(0.0069)
ln_machine_car_build (25)	0.0769***	0.6500***	0.2924***	-0.1130***
	(0.0044)	(0.0232)	(0.0160)	(0.0078)
ln_electrical_engineer (26)	0.3022***	0.6261***	0.5344***	-0.0265
	(0.0080)	(0.0187)	(0.0200)	(0.0181)
ln_tech_research_construction (27)	0.2605***	0.5675***	0.4747***	-0.2068***
	(0.0056)	(0.0115)	(0.0140)	(0.0257)
ln_textile_process (28)	-0.4062***	-0.6391***	-0.2653***	-0.3877***
	(0.0186)	(0.1189)	(0.0591)	(0.0245)
ln_food_process (29)	-0.4124***	-0.2664*	0.1414**	-0.4822***
	(0.0129)	(0.1062)	(0.0505)	(0.0194)
ln_architecture (31)	0.2186***	0.3186***	0.5518***	-0.3086***
	(0.0116)	(0.0274)	(0.0233)	(0.0511)
ln_construction (32)	-0.7567***	-0.8001***	-0.0674	-0.6148***
	(0.0131)	(0.1017)	(0.0515)	(0.0203)
ln_interior_constr (33)	-0.5126***	-0.7495***	0.0062	-0.5158***
	(0.0126)	(0.1177)	(0.0527)	(0.0220)
ln_build_engineer (34)	-0.1721***	0.1238	0.0914*	-0.2697***
	(0.0092)	(0.0706)	(0.0381)	(0.0136)
ln_math_bio_chem (41)	0.1621***	0.5793***	0.3525***	-0.0563
	(0.0078)	(0.0178)	(0.0181)	(0.0290)
ln_geo (42)	-0.1644***	-0.3412***	0.1297	-0.5412*
	(0.0382)	(0.0887)	(0.0966)	(0.2596)
ln_IT (43)	0.5008***	0.8611***	0.7688***	-0.1707***

Dependent variable: log daily wage	Occupation specific coeffi-cients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 79* (11)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 90* (12)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 00* (13)
	(0.0134)	(0.0249)	(0.0217)	(0.0284)
ln_logistics (51)	-0.1368***	0.1615***	0.1439***	-0.3338***
	(0.0059)	(0.0235)	(0.0153)	(0.0150)
ln_drivers (52)	-0.5455***	-0.0667	0.0915*	-0.4988***
	(0.0100)	(0.1043)	(0.0465)	(0.0142)
ln_safety (53)	-0.0848***	0.2890***	0.2453***	-0.3336***
	(0.0101)	(0.0278)	(0.0205)	(0.0371)
ln_cleaning_service (54)	-0.5152***	0.0755	0.2422**	-0.5857***
	(0.0450)	(0.1334)	(0.0741)	(0.0596)
ln_purchasing_sales (61)	0.2612***	0.6091***	0.5124***	-0.2602***
	(0.0074)	(0.0169)	(0.0151)	(0.0255)
ln_retail (62)	-0.1683***	0.0963*	0.2617***	-0.4349***
	(0.0087)	(0.0441)	(0.0190)	(0.0166)
ln_tourism (63)	-0.4832***	-0.4562***	0.0209	-0.3839***
	(0.0184)	(0.0842)	(0.0345)	(0.0377)
ln_management (71)	0.1255***	0.2968***	0.5257***	-0.2117***
	(0.0041)	(0.0077)	(0.0106)	(0.0213)
ln_finance (72)	0.3978***	0.5358***	0.7681***	-0.2638***
	(0.0074)	(0.0096)	(0.0186)	(0.0317)
ln_law (73)	0.2398***	0.5347***	0.5633***	-0.1643**
	(0.0172)	(0.0488)	(0.0265)	(0.0591)
ln_medical (81)	-0.1445***	0.0874**	0.1877***	-0.3229***
	(0.0069)	(0.0316)	(0.0111)	(0.0214)
ln_wellness (82)	-0.5366***	-0.0362	0.1958***	-0.6207***
	(0.0265)	(0.2213)	(0.0485)	(0.0391)
ln_education (83)	0.0592***	0.3773***	0.4201***	-0.1733***
	(0.0076)	(0.0990)	(0.0158)	(0.0151)
ln_teaching (84)	0.1993***	0.7042***	0.4696***	-0.1395***
	(0.0115)	(0.0526)	(0.0197)	(0.0406)
ln_social_science (91)	0.3833***	1.0902***	0.8187***	-0.2261**
	(0.0297)	(0.0799)	(0.0510)	(0.0760)
ln_marketing (92)	0.3245***	0.5930***	0.7196***	-0.1677**
	(0.0191)	(0.0351)	(0.0498)	(0.0546)
ln_craftwork (93)	-0.1948***	0.1469	0.0249	-0.5084***
	(0.0217)	(0.1301)	(0.0428)	(0.0515)
ln_entertainment (94)	0.0467	0.2572	0.4715***	-0.141
	(0.0328)	(0.1989)	(0.1012)	(0.0740)
ln_age	1.3144***	1.7725***	1.2068***	1.3760***
	(0.0049)	(0.0081)	(0.0087)	(0.0154)
lvl_of_performance	0.1215***	0.0763***	0.0728***	0.0873***
	(0.0016)	(0.0026)	(0.0022)	(0.0036)
ln_formerjobs	0.0267***	0.0546***	0.0441***	0.0087***
	(0.0006)	(0.0010)	(0.0008)	(0.0014)
days_unemployed	-0.0002***	0.0001	-0.0002***	-0.0001***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) subsample 79* (11)	Occupation specific coefficients of log tech age *(KldB2010) subsample 90* (12)	Occupation specific coefficients of log tech age *(KldB2010) subsample 00* (13)
	0.0000	(0.0001)	0.0000	0.0000
ln_experience	0.0798***	0.0636***	0.0575***	0.0344***
	(0.0003)	(0.0006)	(0.0004)	(0.0006)
0.vocTrain	0	0	0	0
	(.)	(.)	(.)	(.)
1.vocTrain	-0.0564***	-0.0397	-0.0816**	-0.0892*
	(0.0164)	(0.0250)	(0.0296)	(0.0445)
2.vocTrain	-0.0099	-0.0071	-0.045	0.0826
	(0.0163)	(0.0249)	(0.0295)	(0.0442)
3.vocTrain	-0.0948***	-0.05	-0.1162***	-0.0784
	(0.0168)	(0.0257)	(0.0302)	(0.0454)
4.vocTrain	0.0661***	0.0525*	0.009	0.1451**
	(0.0165)	(0.0253)	(0.0297)	(0.0445)
5.vocTrain	0.2235***	0.1920***	0.1161***	0.2552***
	(0.0165)	(0.0254)	(0.0298)	(0.0445)
11.KldB2010	0	0	0	0
	(.)	(.)	(.)	(.)
12.KldB2010	-0.0001	0.0067	0.0261**	0.0151
	(0.0053)	(0.0091)	(0.0101)	(0.0134)
21.KldB2010	0.1606***	0.1551***	0.1715***	0.0924***
	(0.0053)	(0.0086)	(0.0109)	(0.0141)
22.KldB2010	0.0900***	0.1016***	0.1135***	0.0641***
	(0.0049)	(0.0082)	(0.0095)	(0.0119)
23.KldB2010	0.1142***	0.0989***	0.1062***	0.1579***
	(0.0057)	(0.0091)	(0.0116)	(0.0161)
24.KldB2010	0.0740***	0.1096***	0.1064***	0.0371**
	(0.0047)	(0.0080)	(0.0092)	(0.0113)
25.KldB2010	0.0432***	0.0518***	0.0494***	0.0326**
	(0.0048)	(0.0082)	(0.0092)	(0.0114)
26.KldB2010	0.0353***	0.0224*	-0.0222*	0.0544***
	(0.0054)	(0.0091)	(0.0105)	(0.0137)
27.KldB2010	0.0403***	0.0376***	-0.0568***	0.1492***
	(0.0053)	(0.0086)	(0.0106)	(0.0171)
28.KldB2010	0.0419***	0.0518***	0.0563***	0.025
	(0.0055)	(0.0088)	(0.0103)	(0.0146)
29.KldB2010	0.0340***	0.0497***	0.0532***	0.002
	(0.0051)	(0.0084)	(0.0095)	(0.0123)
31.KldB2010	0.0479***	0.0625***	-0.0876***	0.2101***
	(0.0077)	(0.0120)	(0.0147)	(0.0304)
32.KldB2010	0.1509***	0.1417***	0.1595***	0.0882***
	(0.0048)	(0.0081)	(0.0092)	(0.0115)
33.KldB2010	0.1172***	0.1180***	0.1295***	0.0997***
	(0.0051)	(0.0086)	(0.0097)	(0.0125)
34.KldB2010	0.0797***	0.0994***	0.0957***	0.0502***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) subsample 79* (11)	Occupation specific coefficients of log tech age *(KldB2010) subsample 90* (12)	Occupation specific coefficients of log tech age *(KldB2010) subsample 00* (13)
	(0.0051)	(0.0086)	(0.0098)	(0.0124)
41.KldB2010	0.0616***	0.0524***	0.0053	0.0735***
	(0.0057)	(0.0092)	(0.0112)	(0.0189)
42.KldB2010	0.3550***	0.2560***	0.3354***	0.5204***
	(0.0324)	(0.0572)	(0.0634)	(0.1179)
43.KldB2010	-0.0557***	-0.2377***	-0.2317***	0.1358***
	(0.0083)	(0.0151)	(0.0143)	(0.0180)
51.KldB2010	0.0887***	0.0912***	0.0717***	0.0768***
	(0.0048)	(0.0081)	(0.0092)	(0.0121)
52.KldB2010	0.0714***	0.1090***	0.0894***	0.0077
	(0.0048)	(0.0081)	(0.0092)	(0.0115)
53.KldB2010	0.0644***	0.0388***	-0.0103	0.1291***
	(0.0062)	(0.0097)	(0.0119)	(0.0227)
54.KldB2010	-0.0169**	0.0437***	0.0392***	-0.1053***
	(0.0052)	(0.0088)	(0.0098)	(0.0125)
61.KldB2010	0.0798***	0.0578***	-0.0387***	0.1675***
	(0.0056)	(0.0088)	(0.0107)	(0.0165)
62.KldB2010	0.0358***	0.0221**	0.0098	0.0723***
	(0.0050)	(0.0084)	(0.0094)	(0.0123)
63.KldB2010	0.0689***	0.0544***	0.0352***	-0.0013
	(0.0060)	(0.0096)	(0.0107)	(0.0164)
71.KldB2010	0.0758***	0.0559***	-0.1107***	0.1412***
	(0.0050)	(0.0084)	(0.0099)	(0.0153)
72.KldB2010	0.0527***	-0.0029	-0.1810***	0.2545***
	(0.0062)	(0.0095)	(0.0127)	(0.0191)
73.KldB2010	0.0848***	0.0671***	-0.0727***	0.1389***
	(0.0095)	(0.0145)	(0.0153)	(0.0339)
81.KldB2010	0.1747***	0.1260***	0.0887***	0.1885***
	(0.0060)	(0.0099)	(0.0102)	(0.0158)
82.KldB2010	-0.1600***	-0.2305***	-0.1729***	-0.0477*
	(0.0087)	(0.0134)	(0.0136)	(0.0207)
83.KldB2010	0.0343***	0.0334***	0.0621***	0.0156
	(0.0057)	(0.0094)	(0.0100)	(0.0139)
84.KldB2010	0.0093	0.0258*	-0.0177	0.0541*
	(0.0073)	(0.0124)	(0.0122)	(0.0239)
91.KldB2010	-0.0117	-0.0788***	-0.2340***	0.1341***
	(0.0138)	(0.0200)	(0.0247)	(0.0371)
92.KldB2010	0.0365***	0.0121	-0.1880***	0.1252***
	(0.0106)	(0.0144)	(0.0262)	(0.0300)
93.KldB2010	0.0732***	0.0710***	0.0771***	0.1523***
	(0.0080)	(0.0116)	(0.0135)	(0.0261)
94.KldB2010	0.1641***	0.2000***	0.0970***	0.1095**
	(0.0127)	(0.0223)	(0.0235)	(0.0358)
1.industry	0	0	0	0

Dependent variable: log daily wage	Occupation specific coeffi-cients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coeffi-cients of log tech age *(KldB2010)* *subsample 79* (11)	Occupation specific coeffi-cients of log tech age *(KldB2010)* *subsample 90* (12)	Occupation specific coeffi-cients of log tech age *(KldB2010)* *subsample 00* (13)
	(.)	(.)	(.)	(.)
2.industry	0.0926***	0.0632***	0.0708***	0.1184***
	(0.0029)	(0.0050)	(0.0039)	(0.0062)
3.industry	0.0886***	0.0640***	0.0699***	0.1281***
	(0.0027)	(0.0047)	(0.0036)	(0.0057)
4.industry	0.1232***	0.0948***	0.0888***	0.1472***
	(0.0028)	(0.0048)	(0.0037)	(0.0059)
5.industry	0.0378***	0.0126**	0.0298***	0.0796***
	(0.0027)	(0.0047)	(0.0036)	(0.0058)
6.industry	-0.1898***	-0.1827***	-0.1807***	-0.1365***
	(0.0035)	(0.0058)	(0.0048)	(0.0077)
7.industry	0.0173***	0.0045	0.0294***	0.0637***
	(0.0027)	(0.0047)	(0.0035)	(0.0056)
8.industry	-0.0117***	-0.0409***	-0.0084*	0.0443***
	(0.0026)	(0.0046)	(0.0035)	(0.0055)
9.industry	-0.0163***	-0.0306***	-0.0111**	0.0155**
	(0.0029)	(0.0051)	(0.0038)	(0.0059)
10.industry	-0.0516***	-0.0446***	-0.0597***	-0.0498***
	(0.0027)	(0.0048)	(0.0035)	(0.0055)
11.industry	-0.0163***	-0.0554***	-0.0123**	-0.0117
	(0.0030)	(0.0054)	(0.0039)	(0.0062)
12.industry	0.0042	-0.0152**	0.0027	-0.0164**
	(0.0030)	(0.0054)	(0.0039)	(0.0063)
13.industry	0.0477***	-0.0106*	0.0339***	0.0538***
	(0.0028)	(0.0048)	(0.0037)	(0.0065)
1.state	0	0	0	0
	(.)	(.)	(.)	(.)
2.state	0.0692***	0.0568***	0.0462***	0.0273***
	(0.0033)	(0.0050)	(0.0048)	(0.0063)
3.state	-0.0100**	-0.0168**	-0.003	-0.0105
	(0.0036)	(0.0058)	(0.0051)	(0.0068)
4.state	0.0279***	0.0219**	0.0281***	0.0142
	(0.0049)	(0.0078)	(0.0071)	(0.0098)
5.state	0.0285***	0.0096	0.0271***	0.0088
	(0.0036)	(0.0058)	(0.0052)	(0.0067)
6.state	0.0606***	0.0276***	0.0491***	0.0344***
	(0.0038)	(0.0062)	(0.0055)	(0.0071)
7.state	-0.0123**	-0.0283***	-0.0002	-0.0157*
	(0.0042)	(0.0068)	(0.0061)	(0.0079)
8.state	0.0454***	0.0117	0.0428***	0.0289***
	(0.0038)	(0.0061)	(0.0054)	(0.0071)
9.state	0.0426***	-0.0027	0.0348***	0.0313***
	(0.0038)	(0.0062)	(0.0055)	(0.0070)
10.state	-0.0324***	-0.0574***	-0.0269**	-0.0466***

Dependent variable: log daily wage	Occupation specific coeffi-cients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 79* (11)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 90* (12)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 00* (13)
	(0.0064)	(0.0099)	(0.0098)	(0.0117)
11.state	-0.0276***	0.0116	-0.0556***	-0.0926***
	(0.0042)	(0.0077)	(0.0059)	(0.0077)
12.state	-0.1526***		-0.1614***	-0.1583***
	(0.0045)		(0.0060)	(0.0079)
13.state	-0.1857***		-0.1940***	-0.1674***
	(0.0052)		(0.0066)	(0.0087)
14.state	-0.1931***		-0.1890***	-0.1905***
	(0.0044)		(0.0060)	(0.0078)
15.state	-0.1928***		-0.1870***	-0.1865***
	(0.0047)		(0.0061)	(0.0081)
16.state	-0.1931***		-0.2003***	-0.1773***
	(0.0049)		(0.0065)	(0.0083)
1979.year	0	0		
	(.)	(.)		
1980.year	-0.0147***	-0.0218***		
	(0.0005)	(0.0006)		
1981.year	-0.0199***	-0.0379***		
	(0.0007)	(0.0009)		
1982.year	-0.0411***	-0.0712***		
	(0.0008)	(0.0011)		
1983.year	-0.0626***	-0.1048***		
	(0.0009)	(0.0013)		
1984.year	-0.0600***	-0.1147***		
	(0.0010)	(0.0015)		
1985.year	-0.0647***	-0.1323***		
	(0.0011)	(0.0018)		
1986.year	-0.0715***	-0.1508***		
	(0.0012)	(0.0020)		
1987.year	-0.0764***	-0.1697***		
	(0.0013)	(0.0022)		
1988.year	-0.0899***	-0.1961***		
	(0.0014)	(0.0025)		
1989.year	-0.0902***	-0.2084***		
	(0.0015)	(0.0028)		
1990.year	-0.0679***		0	
	(0.0016)		(.)	
1991.year	-0.0424***		0.0241***	
	(0.0018)		(0.0005)	
1992.year	-0.0369***		0.0273***	
	(0.0019)		(0.0007)	
1993.year	-0.0327***		0.0319***	
	(0.0020)		(0.0010)	
1994.year	-0.0467***		0.0180***	

Dependent variable: log daily wage	Occupation specific coeffi-cients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 79* (11)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 90* (12)	Occupation specific coeffi-cients of log tech age *(KldB2010) subsample 00* (13)
	(0.0021)		(0.0012)	
1995.year	-0.0517***		0.0136***	
	(0.0023)		(0.0015)	
1996.year	-0.0746***		-0.0082***	
	(0.0024)		(0.0018)	
1997.year	-0.1038***		-0.0352***	
	(0.0025)		(0.0020)	
1998.year	-0.1343***		-0.0627***	
	(0.0026)		(0.0023)	
1999.year	-0.1477***		-0.0749***	
	(0.0028)		(0.0026)	
2000.year	-0.1607***			0
	(0.0029)			(.)
2001.year	-0.1668***			-0.0015*
	(0.0031)			(0.0006)
2002.year	-0.1814***			-0.0098***
	(0.0032)			(0.0010)
2003.year	-0.2042***			-0.0263***
	(0.0034)			(0.0014)
2004.year	-0.2324***			-0.0474***
	(0.0035)			(0.0018)
2005.year	-0.2591***			-0.0662***
	(0.0036)			(0.0022)
2006.year	-0.2816***			-0.0797***
	(0.0038)			(0.0026)
employment_change	0.0068***	-0.0042***	0.0089***	0.0058***
	(0.0005)	(0.0008)	(0.0006)	(0.0014)
_cons	-0.8612***	-2.5984***	-0.4021***	-0.8950***
	(0.0233)	(0.0380)	(0.0432)	(0.0703)
N	11,597,284	4,031,135	4,584,849	2,981,300
R-sq	0.5145	0.3895	0.2625	0.1025

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A13.iii. Regression extended sample using *KldB2010* - full output table

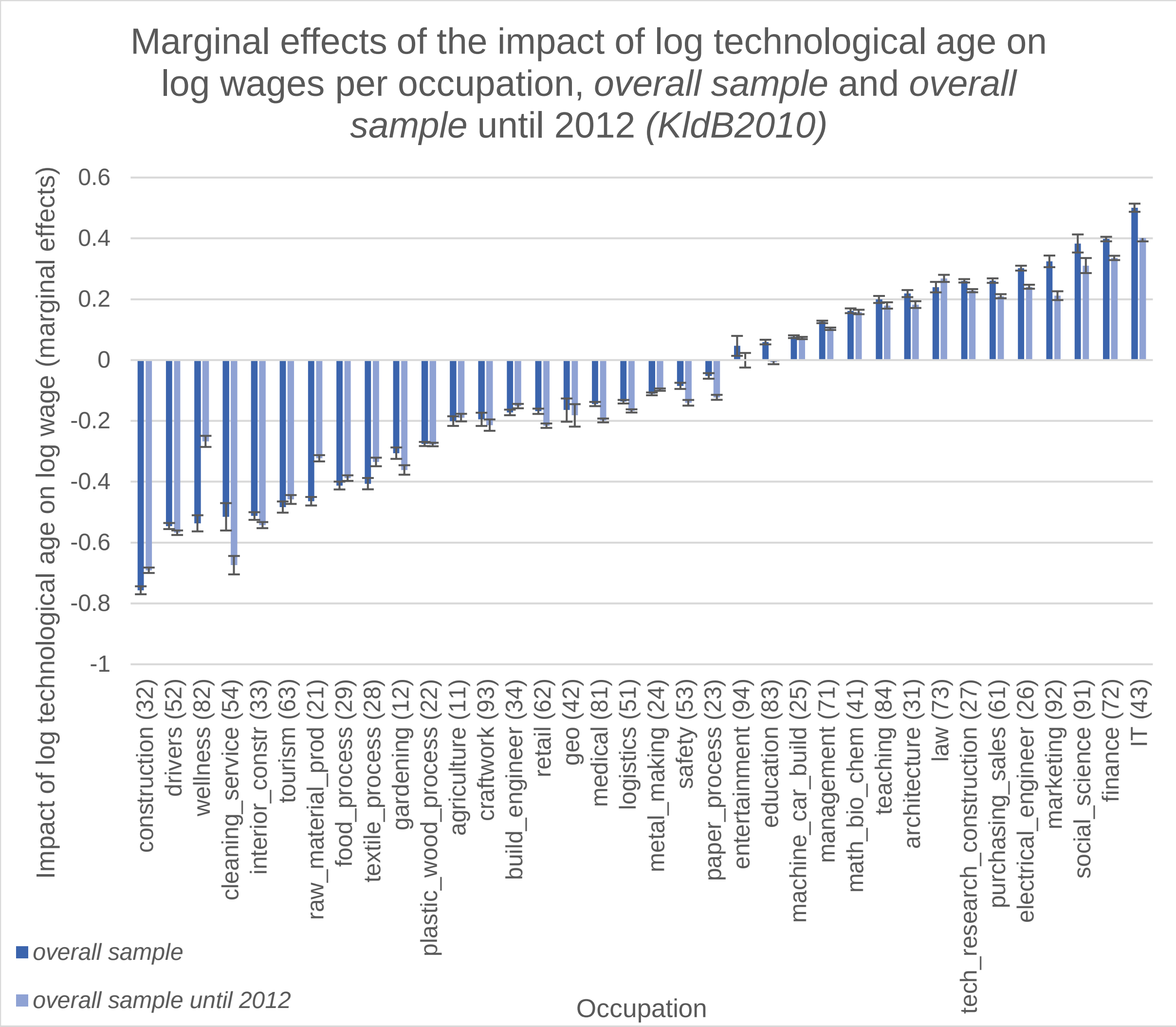

Figure A8: *Marginal effects of the impact of log technological age on log wages per occupation, overall sample and overall sample until 2012 (KldB2010)*

Note: Marginal effects of regression (10) and regression (14), ordered by size of marginal effects in regression (10) Including standard errors. Regression (10) and (14) can be found in Table A56.

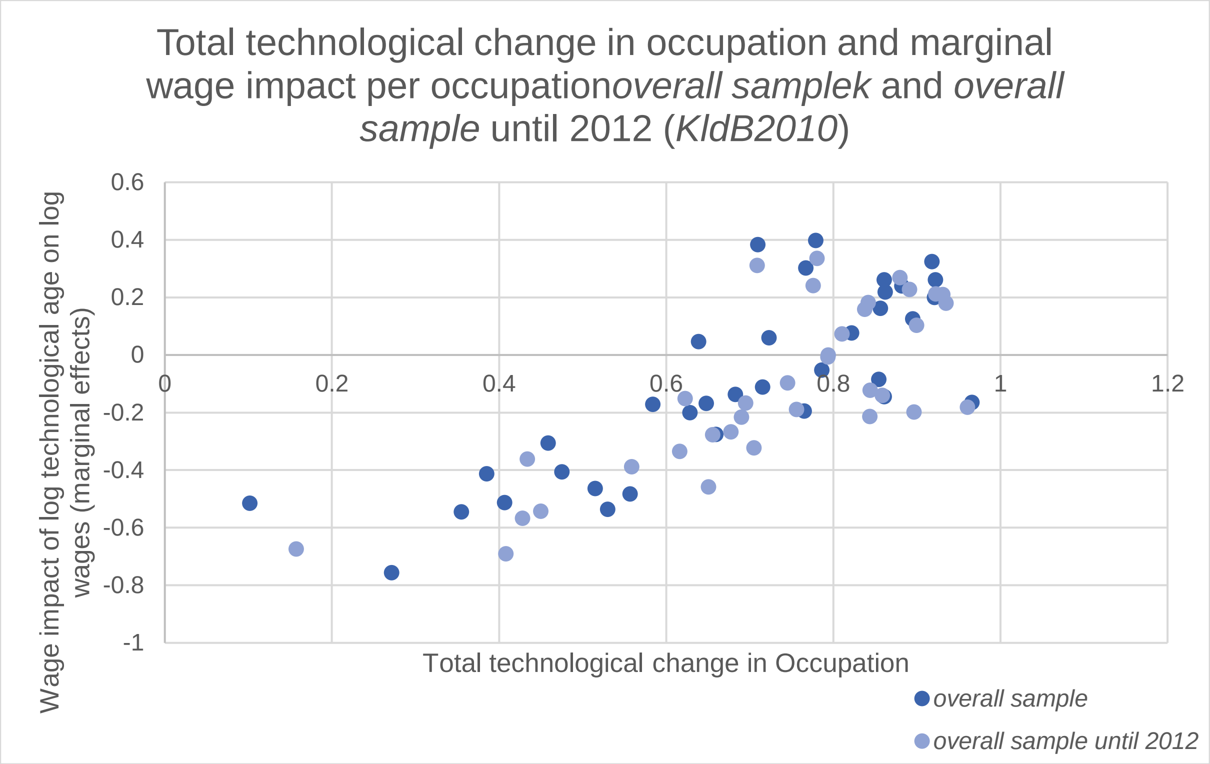

Figure A9: *Total technological change in occupation and marginal wage impact per occupation overall sample and overall sample until 2012 (KldB2010)*

Note: Marginal effects of regression (10), regression (14), and overall technological change per occupation in each timeframe according to Table A11 to Table A15. Regression (10) and (14) can be found in Table A56.

Table A56: *Regressions (10) and (14), the impact of log technological age on log wages, overall sample and overall sample until 2010, KldB2010, full output table*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) overall sample* until 2012 (14)
ln_agriculture (11)	-0.2006***	-0.1891***
	(0.0158)	(0.0124)
ln_gardening (12)	-0.3060***	-0.3612***
	(0.0187)	(0.0156)
ln_raw_material_prod (21)	-0.4640***	-0.3228***
	(0.0140)	(0.0103)
ln_plastic_wood_process (22)	-0.2758***	-0.2775***
	(0.0068)	(0.0058)
ln_paper_process (23)	-0.0521***	-0.1225***
	(0.0092)	(0.0082)
ln_metal_making (24)	-0.1111***	-0.0972***
	(0.0046)	(0.0038)
ln_machine_car_build (25)	0.0769***	0.0725***
	(0.0044)	(0.0037)
ln_electrical_engineer (26)	0.3022***	0.2411***
	(0.0080)	(0.0066)
ln_tech_research_construction (27)	0.2605***	0.2281***
	(0.0056)	(0.0052)
ln_textile_process (28)	-0.4062***	-0.3349***
	(0.0186)	(0.0141)
ln_food_process (29)	-0.4124***	-0.3880***
	(0.0129)	(0.0092)
ln_architecture (31)	0.2186***	0.1824***
	(0.0116)	(0.0111)
ln_construction (32)	-0.7567***	-0.6909***
	(0.0131)	(0.0089)
ln_interior_constr (33)	-0.5126***	-0.5425***
	(0.0126)	(0.0100)
ln_build_engineer (34)	-0.1721***	-0.1513***
	(0.0092)	(0.0072)
ln_math_bio_chem (41)	0.1621***	0.1581***
	(0.0078)	(0.0073)
ln_geo (42)	-0.1644***	-0.1818***
	(0.0382)	(0.0369)
ln_IT (43)	0.5008***	0.4010***
	(0.0134)	(0.0108)
ln_logistics (51)	-0.1368***	-0.1671***
	(0.0059)	(0.0052)
ln_drivers (52)	-0.5455***	-0.5675***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) overall sample* until 2012 (14)
	(0.0100)	(0.0075)
ln_safety (53)	-0.0848***	-0.1404***
	(0.0101)	(0.0093)
ln_cleaning_service (54)	-0.5152***	-0.6742***
	(0.0450)	(0.0303)
ln_purchasing_sales (61)	0.2612***	0.2100***
	(0.0074)	(0.0067)
ln_retail (62)	-0.1683***	-0.2157***
	(0.0087)	(0.0073)
ln_tourism (63)	-0.4832***	-0.4583***
	(0.0184)	(0.0145)
ln_management (71)	0.1255***	0.1029***
	(0.0041)	(0.0040)
ln_finance (72)	0.3978***	0.3358***
	(0.0074)	(0.0071)
ln_law (73)	0.2398***	0.2686***
	(0.0172)	(0.0117)
ln_medical (81)	-0.1445***	-0.1984***
	(0.0069)	(0.0063)
ln_wellness (82)	-0.5366***	-0.2673***
	(0.0265)	(0.0183)
ln_education (83)	0.0592***	-0.0072
	(0.0076)	(0.0064)
ln_teaching (84)	0.1993***	0.1796***
	(0.0115)	(0.0104)
ln_social_science (91)	0.3833***	0.3107***
	(0.0297)	(0.0247)
ln_marketing (92)	0.3245***	0.2117***
	(0.0191)	(0.0145)
ln_craftwork (93)	-0.1948***	-0.2138***
	(0.0217)	(0.0187)
ln_entertainment (94)	0.0467	-0.0006
	(0.0328)	(0.0240)
ln_age	1.3144***	1.2845***
	(0.0049)	(0.0046)
lvl_of_performance	0.1215***	0.1338***
	(0.0016)	(0.0013)
ln_formerjobs	0.0267***	0.0112***
	(0.0006)	(0.0005)
days_unemployed	-0.0002***	-0.0002***
	0.0000	0.0000
ln_experience	0.0798***	0.0706***
	(0.0003)	(0.0003)
0.vocTrain	0	0

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010) overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) overall sample* until 2012 (14)
	(.)	(.)
1.vocTrain	-0.0564***	-0.0024
	(0.0164)	(0.0158)
2.vocTrain	-0.0099	0.0518**
	(0.0163)	(0.0157)
3.vocTrain	-0.0948***	-0.0465**
	(0.0168)	(0.0161)
4.vocTrain	0.0661***	0.1264***
	(0.0165)	(0.0158)
5.vocTrain	0.2235***	0.2856***
	(0.0165)	(0.0159)
11.KldB2010	0	0
	(.)	(.)
12.KldB2010	-0.0001	0.0049
	(0.0053)	(0.0052)
21.KldB2010	0.1606***	0.1555***
	(0.0053)	(0.0052)
22.KldB2010	0.0900***	0.0898***
	(0.0049)	(0.0047)
23.KldB2010	0.1142***	0.1233***
	(0.0057)	(0.0055)
24.KldB2010	0.0740***	0.0625***
	(0.0047)	(0.0045)
25.KldB2010	0.0432***	0.0296***
	(0.0048)	(0.0046)
26.KldB2010	0.0353***	0.0257***
	(0.0054)	(0.0051)
27.KldB2010	0.0403***	0.0282***
	(0.0053)	(0.0050)
28.KldB2010	0.0419***	0.0444***
	(0.0055)	(0.0054)
29.KldB2010	0.0340***	0.0341***
	(0.0051)	(0.0048)
31.KldB2010	0.0479***	0.0397***
	(0.0077)	(0.0074)
32.KldB2010	0.1509***	0.1623***
	(0.0048)	(0.0046)
33.KldB2010	0.1172***	0.1301***
	(0.0051)	(0.0049)
34.KldB2010	0.0797***	0.0772***
	(0.0051)	(0.0049)
41.KldB2010	0.0616***	0.0428***
	(0.0057)	(0.0055)
42.KldB2010	0.3550***	0.3503***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (KldB2010) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) overall sample* until 2012 (14)
	(0.0324)	(0.0258)
43.KldB2010	-0.0557***	-0.0276***
	(0.0083)	(0.0069)
51.KldB2010	0.0887***	0.0837***
	(0.0048)	(0.0046)
52.KldB2010	0.0714***	0.0670***
	(0.0048)	(0.0046)
53.KldB2010	0.0644***	0.0694***
	(0.0062)	(0.0060)
54.KldB2010	-0.0169**	-0.0314***
	(0.0052)	(0.0050)
61.KldB2010	0.0798***	0.0802***
	(0.0056)	(0.0053)
62.KldB2010	0.0358***	0.0442***
	(0.0050)	(0.0048)
63.KldB2010	0.0689***	0.0678***
	(0.0060)	(0.0057)
71.KldB2010	0.0758***	0.0706***
	(0.0050)	(0.0048)
72.KldB2010	0.0527***	0.0701***
	(0.0062)	(0.0059)
73.KldB2010	0.0848***	0.0701***
	(0.0095)	(0.0073)
81.KldB2010	0.1747***	0.1786***
	(0.0060)	(0.0056)
82.KldB2010	-0.1600***	-0.0678***
	(0.0087)	(0.0078)
83.KldB2010	0.0343***	0.0026
	(0.0057)	(0.0054)
84.KldB2010	0.0093	-0.0086
	(0.0073)	(0.0069)
91.KldB2010	-0.0117	-0.0252*
	(0.0138)	(0.0119)
92.KldB2010	0.0365***	0.0595***
	(0.0106)	(0.0082)
93.KldB2010	0.0732***	0.0825***
	(0.0080)	(0.0078)
94.KldB2010	0.1641***	0.1573***
	(0.0127)	(0.0116)
1.industry	0	0
	(.)	(.)
2.industry	0.0926***	0.1057***
	(0.0029)	(0.0028)
3.industry	0.0886***	0.1023***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010) overall sample* until 2012 (14)
	(0.0027)	(0.0026)
4.industry	0.1232***	0.1376***
	(0.0028)	(0.0027)
5.industry	0.0378***	0.0472***
	(0.0027)	(0.0026)
6.industry	-0.1898***	-0.1854***
	(0.0035)	(0.0034)
7.industry	0.0173***	0.0201***
	(0.0027)	(0.0026)
8.industry	-0.0117***	-0.0021
	(0.0026)	(0.0026)
9.industry	-0.0163***	-0.0116***
	(0.0029)	(0.0028)
10.industry	-0.0516***	-0.0536***
	(0.0027)	(0.0026)
11.industry	-0.0163***	-0.0165***
	(0.0030)	(0.0029)
12.industry	0.0042	0.0061*
	(0.0030)	(0.0029)
13.industry	0.0477***	0.0571***
	(0.0028)	(0.0028)
1.state	0	0
	(.)	(.)
2.state	0.0692***	0.0684***
	(0.0033)	(0.0030)
3.state	-0.0100**	-0.0135***
	(0.0036)	(0.0033)
4.state	0.0279***	0.0269***
	(0.0049)	(0.0046)
5.state	0.0285***	0.0269***
	(0.0036)	(0.0033)
6.state	0.0606***	0.0588***
	(0.0038)	(0.0035)
7.state	-0.0123**	-0.0134***
	(0.0042)	(0.0039)
8.state	0.0454***	0.0450***
	(0.0038)	(0.0035)
9.state	0.0426***	0.0441***
	(0.0038)	(0.0034)
10.state	-0.0324***	-0.0290***
	(0.0064)	(0.0059)
11.state	-0.0276***	-0.0351***
	(0.0042)	(0.0039)
12.state	-0.1526***	-0.1519***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010)* *overall sample* until 2012 (14)
	(0.0045)	(0.0041)
13.state	-0.1857***	-0.1865***
	(0.0052)	(0.0047)
14.state	-0.1931***	-0.1968***
	(0.0044)	(0.0040)
15.state	-0.1928***	-0.1931***
	(0.0047)	(0.0042)
16.state	-0.1931***	-0.1940***
	(0.0049)	(0.0044)
1979.year	0	0
	(.)	(.)
1980.year	-0.0147***	-0.0074***
	(0.0005)	(0.0005)
1981.year	-0.0199***	-0.0077***
	(0.0007)	(0.0006)
1982.year	-0.0411***	-0.0247***
	(0.0008)	(0.0007)
1983.year	-0.0626***	-0.0429***
	(0.0009)	(0.0008)
1984.year	-0.0600***	-0.0374***
	(0.0010)	(0.0009)
1985.year	-0.0647***	-0.0393***
	(0.0011)	(0.0010)
1986.year	-0.0715***	-0.0434***
	(0.0012)	(0.0011)
1987.year	-0.0764***	-0.0457***
	(0.0013)	(0.0012)
1988.year	-0.0899***	-0.0565***
	(0.0014)	(0.0013)
1989.year	-0.0902***	-0.0543***
	(0.0015)	(0.0014)
1990.year	-0.0679***	-0.0298***
	(0.0016)	(0.0015)
1991.year	-0.0424***	-0.0016
	(0.0018)	(0.0016)
1992.year	-0.0369***	0.0041*
	(0.0019)	(0.0018)
1993.year	-0.0327***	0.0121***
	(0.0020)	(0.0019)
1994.year	-0.0467***	0.0012
	(0.0021)	(0.0020)
1995.year	-0.0517***	-0.0009
	(0.0023)	(0.0021)
1996.year	-0.0746***	-0.0211***

Dependent variable: log daily wage	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (10)	Occupation specific coefficients of log tech age *(KldB2010)* *overall sample* until 2012 (14)
	(0.0024)	(0.0022)
1997.year	-0.1038***	-0.0483***
	(0.0025)	(0.0023)
1998.year	-0.1343***	-0.0768***
	(0.0026)	(0.0025)
1999.year	-0.1477***	-0.0879***
	(0.0028)	(0.0026)
2000.year	-0.1607***	-0.0988***
	(0.0029)	(0.0027)
2001.year	-0.1668***	-0.1028***
	(0.0031)	(0.0028)
2002.year	-0.1814***	-0.1156***
	(0.0032)	(0.0030)
2003.year	-0.2042***	-0.1367***
	(0.0034)	(0.0031)
2004.year	-0.2324***	-0.1639***
	(0.0035)	(0.0032)
2005.year	-0.2591***	-0.1895***
	(0.0036)	(0.0034)
2006.year	-0.2816***	-0.2093***
	(0.0038)	(0.0035)
2007.year		-0.2223***
		(0.0036)
2008.year		-0.2489***
		(0.0037)
2009.year		-0.2502***
		(0.0038)
2010.year		-0.2632***
		(0.0039)
2011.year		-0.2276***
		(0.0040)
2012.year		-0.2226***
		(0.0041)
employment_change	0.0068***	0.0067***
	(0.0005)	(0.0004)
_cons	-0.8612***	-0.7733***
	(0.0233)	(0.0219)
N	11,597,284	13,965,569
R-sq	0.5145	0.5057

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A13.iv. Regression *overall sample* imputed starting technological age - full output table

Table A57: *Regressions (1) and (15), the impact of log technological age on log wages, overall sample and overall sample with imputed technological age, full output table*

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (15)
ln_agriculture_fishing (1)	-0.2747***	-0.2693***
	(0.0113)	(0.0114)
ln_miners_stone_workers (2)	-0.4973***	-0.4999***
	(0.0172)	(0.0176)
ln_ceramic_glas (3)	-0.3295***	-0.3281***
	(0.0221)	(0.0221)
ln_chemistry_synthetic_workers (4)	-0.1028***	-0.1037***
	(0.0070)	(0.0071)
ln_paper_print (5)	-0.0943***	-0.1045***
	(0.0104)	(0.0105)
ln_woodworking (6)	-0.1033	-0.0488
	(0.0920)	(0.0970)
ln_metal_works (7)	-0.0850***	-0.0823***
	(0.0055)	(0.0056)
ln_mechanics (8)	-0.0810***	-0.0750***
	(0.0047)	(0.0047)
ln_electricians (9)	0.0452***	0.0473***
	(0.0067)	(0.0067)
ln_assembly (10)	-0.1107***	-0.1101***
	(0.0078)	(0.0078)
ln_textile_clothing_leather_fur (11)	-0.4416***	-0.4393***
	(0.0213)	(0.0214)
ln_food (12)	-0.4447***	-0.4303***
	(0.0133)	(0.0134)
ln_construction (13)	-0.7668***	-0.7670***
	(0.0122)	(0.0123)
ln_interior_construction (14)	-0.4682***	-0.4653***
	(0.0147)	(0.0148)
ln_carpenter (15)	-0.4003***	-0.3948***
	(0.0119)	(0.0120)
ln_painter (16)	-0.3426***	-0.3373***
	(0.0123)	(0.0124)
ln_product_testing (17)	-0.0773***	-0.0708***
	(0.0087)	(0.0088)
ln_machinist (18)	-0.0528***	-0.0498***
	(0.0090)	(0.0090)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (15)
ln_engineer_math_chem (19)	0.3367***	0.3175***
	(0.0090)	(0.0092)
ln_technical_specilaist (20)	0.3143***	0.3196***
	(0.0054)	(0.0054)
ln_goods_merchants (21)	0.0389***	0.0628***
	(0.0071)	(0.0071)
ln_service_merchants (22)	0.3714***	0.3852***
	(0.0075)	(0.0075)
ln_traffic (23)	-0.3411***	-0.3391***
	(0.0060)	(0.0060)
ln_administration (24)	0.1746***	0.1759***
	(0.0043)	(0.0043)
ln_regulatory_safety (25)	-0.0975***	-0.0999***
	(0.0097)	(0.0099)
ln_writing_art (26)	0.1741***	0.1848***
	(0.0144)	(0.0145)
ln_healthcare (27)	-0.1575***	-0.1560***
	(0.0070)	(0.0070)
ln_social_education_science (28)	0.1381***	0.1531***
	(0.0079)	(0.0080)
ln_age	1.3427***	1.3434***
	(0.0050)	(0.0050)
lvl_of_performance	0.1351***	0.1352***
	(0.0018)	(0.0018)
ln_formerjobs	0.0233***	0.0238***
	(0.0006)	(0.0006)
days_unemployed	-0.0002***	-0.0002***
	0.0000	0.0000
ln_experience	0.0809***	0.0799***
	(0.0003)	(0.0003)
employment_change	0.0014**	0.0010*
	(0.0005)	(0.0005)
1.vocTrain	0	0
	(.)	(.)
2.vocTrain	0.0510***	0.0513***
	(0.0015)	(0.0015)
3.vocTrain	-0.0407***	-0.0401***
	(0.0044)	(0.0044)
4.vocTrain	0.1214***	0.1227***
	(0.0027)	(0.0027)
5.vocTrain	0.2732***	0.2754***
	(0.0028)	(0.0028)
1.KldB88	0	0
	(.)	(.)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (15)
2.KldB88	0.1694***	0.1712***
	(0.0044)	(0.0045)
4.KldB88	0.1328***	0.1328***
	(0.0056)	(0.0056)
5.KldB88	0.1097***	0.1081***
	(0.0037)	(0.0037)
6.KldB88	0.1230***	0.1240***
	(0.0046)	(0.0047)
7.KldB88	0.1288***	0.1285***
	(0.0054)	(0.0053)
8.KldB88	0.0949***	0.0929***
	(0.0033)	(0.0034)
9.KldB88	0.0360***	0.0331***
	(0.0032)	(0.0032)
10.KldB88	0.0046	-0.0003
	(0.0037)	(0.0038)
11.KldB88	0.1132***	0.1115***
	(0.0034)	(0.0035)
12.KldB88	0.0318***	0.0330***
	(0.0044)	(0.0044)
14.KldB88	0.0458***	0.0466***
	(0.0037)	(0.0037)
15.KldB88	0.1560***	0.1586***
	(0.0032)	(0.0032)
16.KldB88	0.1359***	0.1367***
	(0.0041)	(0.0042)
17.KldB88	0.0577***	0.0577***
	(0.0042)	(0.0042)
18.KldB88	0.0745***	0.0744***
	(0.0042)	(0.0043)
19.KldB88	0.0893***	0.0866***
	(0.0036)	(0.0036)
21.KldB88	0.1337***	0.1312***
	(0.0038)	(0.0038)
22.KldB88	-0.0373***	-0.0448***
	(0.0056)	(0.0061)
23.KldB88	0.0088*	-0.0059
	(0.0039)	(0.0040)
24.KldB88	0.0634***	0.0550***
	(0.0036)	(0.0036)
25.KldB88	0.0558***	0.0291***
	(0.0051)	(0.0053)
26.KldB88	0.0916***	0.0934***
	(0.0031)	(0.0031)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (15)
27.KldB88	0.0447***	0.0353***
	(0.0037)	(0.0037)
28.KldB88	0.0688***	0.0685***
	(0.0047)	(0.0049)
29.KldB88	0.0737***	0.0626***
	(0.0071)	(0.0073)
30.KldB88	0.1845***	0.1837***
	(0.0049)	(0.0050)
31.KldB88	0.0288***	0.0180***
	(0.0049)	(0.0051)
1.industry	0	0
	(.)	(.)
2.industry	0.0832***	0.0835***
	(0.0030)	(0.0030)
3.industry	0.0815***	0.0820***
	(0.0027)	(0.0027)
4.industry	0.1156***	0.1159***
	(0.0028)	(0.0028)
5.industry	0.0328***	0.0329***
	(0.0027)	(0.0027)
6.industry	-0.2013***	-0.2011***
	(0.0040)	(0.0040)
7.industry	0.0178***	0.0179***
	(0.0027)	(0.0027)
8.industry	-0.0188***	-0.0186***
	(0.0027)	(0.0027)
9.industry	-0.0306***	-0.0305***
	(0.0029)	(0.0029)
10.industry	-0.0496***	-0.0491***
	(0.0027)	(0.0027)
11.industry	-0.004	-0.0036
	(0.0031)	(0.0031)
12.industry	-0.0144***	-0.0141***
	(0.0031)	(0.0031)
13.industry	0.0432***	0.0436***
	(0.0029)	(0.0029)
1.state	0	0
	(.)	(.)
2.state	0.0670***	0.0670***
	(0.0033)	(0.0033)
3.state	-0.0107**	-0.0107**
	(0.0037)	(0.0037)
4.state	0.0292***	0.0293***
	(0.0051)	(0.0051)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (15)
5.state	0.0299***	0.0300***
	(0.0037)	(0.0037)
6.state	0.0607***	0.0607***
	(0.0039)	(0.0039)
7.state	-0.0103*	-0.0104*
	(0.0043)	(0.0043)
8.state	0.0468***	0.0468***
	(0.0039)	(0.0039)
9.state	0.0422***	0.0423***
	(0.0039)	(0.0039)
10.state	-0.0315***	-0.0314***
	(0.0066)	(0.0066)
11.state	-0.0289***	-0.0289***
	(0.0043)	(0.0043)
12.state	-0.1534***	-0.1534***
	(0.0046)	(0.0046)
13.state	-0.1906***	-0.1906***
	(0.0054)	(0.0054)
14.state	-0.1928***	-0.1929***
	(0.0045)	(0.0045)
15.state	-0.1909***	-0.1910***
	(0.0047)	(0.0047)
16.state	-0.1931***	-0.1932***
	(0.0050)	(0.0050)
1979.year	0	0
	(.)	(.)
1980.year	-0.0158***	-0.0150***
	(0.0005)	(0.0005)
1981.year	-0.0231***	-0.0219***
	(0.0007)	(0.0007)
1982.year	-0.0454***	-0.0439***
	(0.0008)	(0.0008)
1983.year	-0.0677***	-0.0659***
	(0.0009)	(0.0009)
1984.year	-0.0657***	-0.0639***
	(0.0010)	(0.0010)
1985.year	-0.0709***	-0.0690***
	(0.0011)	(0.0011)
1986.year	-0.0790***	-0.0769***
	(0.0012)	(0.0012)
1987.year	-0.0851***	-0.0830***
	(0.0013)	(0.0013)
1988.year	-0.0991***	-0.0969***
	(0.0014)	(0.0014)

Dependent variable: log daily wage	Occupation specific coefficients of log tech age *overall sample* (1)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (15)
1989.year	-0.1003***	-0.0981***
	(0.0015)	(0.0015)
1990.year	-0.0789***	-0.0767***
	(0.0017)	(0.0017)
1991.year	-0.0543***	-0.0520***
	(0.0018)	(0.0018)
1992.year	-0.0500***	-0.0478***
	(0.0019)	(0.0019)
1993.year	-0.0468***	-0.0445***
	(0.0020)	(0.0020)
1994.year	-0.0614***	-0.0590***
	(0.0021)	(0.0021)
1995.year	-0.0675***	-0.0650***
	(0.0023)	(0.0023)
1996.year	-0.0904***	-0.0879***
	(0.0024)	(0.0024)
1997.year	-0.1203***	-0.1178***
	(0.0025)	(0.0025)
1998.year	-0.1513***	-0.1488***
	(0.0027)	(0.0027)
1999.year	-0.1653***	-0.1628***
	(0.0028)	(0.0028)
2000.year	-0.1786***	-0.1761***
	(0.0030)	(0.0030)
2001.year	-0.1851***	-0.1827***
	(0.0031)	(0.0031)
2002.year	-0.2003***	-0.1980***
	(0.0032)	(0.0032)
2003.year	-0.2230***	-0.2208***
	(0.0034)	(0.0034)
2004.year	-0.2509***	-0.2487***
	(0.0035)	(0.0035)
2005.year	-0.2782***	-0.2760***
	(0.0037)	(0.0037)
2006.year	-0.3012***	-0.2991***
	(0.0038)	(0.0038)
Constant	-1.0005***	-1.0049***
	(0.0167)	(0.0168)
N	11,012,285	11,012,285
R-sq	0.5218	0.5217

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A13.v. Regression *overall sample,* lagged technological age

***Table A 58**: Regressions (1) and (16), the impact of log technological age on log wages, overall sample and overall sample with technological age lagged one-year, full output table*

Dependent variable: log wage	Occupation specific co-efficients of log tech age *entire sample* (1)	Occupation specific co-efficients of log tech age *entire sample*, lagged technological age (16)
ln_agriculture_fishing (1)	-0.2747***	-0.1357***
	(0.0113)	(0.0113)
ln_miners_stone_workers (2)	-0.4973***	-0.3971***
	(0.0172)	(0.0172)
ln_ceramic_glas (3)	-0.3295***	-0.2361***
	(0.0221)	(0.0223)
ln_chemistry_synthetic_workers (4)	-0.1028***	-0.0326***
	(0.0070)	(0.0068)
ln_paper_print (5)	-0.0943***	-0.0417***
	(0.0104)	(0.0099)
ln_woodworking (6)	-0.1033	0.1080***
	(0.0920)	(0.0312)
ln_metal_works (7)	-0.0850***	-0.0319***
	(0.0055)	(0.0056)
ln_mechanics (8)	-0.0810***	-0.0460***
	(0.0047)	(0.0043)
ln_electricians (9)	0.0452***	0.0816***
	(0.0067)	(0.0062)
ln_assembly (10)	-0.1107***	-0.0218**
	(0.0078)	(0.0077)
ln_textile_clothing_leather_fur (11)	-0.4416***	-0.2707***
	(0.0213)	(0.0205)
ln_food (12)	-0.4447***	-0.2360***
	(0.0133)	(0.0123)
ln_construction (13)	-0.7668***	-0.4016***
	(0.0122)	(0.0098)
ln_interior_construction (14)	-0.4682***	-0.3915***
	(0.0147)	(0.0153)
ln_carpenter (15)	-0.4003***	-0.3718***
	(0.0119)	(0.0120)
ln_painter (16)	-0.3426***	-0.2659***
	(0.0123)	(0.0124)
ln_product_testing (17)	-0.0773***	0.0129
	(0.0087)	(0.0084)
ln_machinist (18)	-0.0528***	-0.0196*
	(0.0090)	(0.0093)
ln_engineer_math_chem (19)	0.3367***	0.2889***

Dependent variable: log wage	Occupation specific co-efficients of log tech age *entire sample* (1)	Occupation specific co-efficients of log tech age *entire sample*, lagged technological age (16)
	(0.0090)	(0.0078)
ln_technical_specilaist (20)	0.3143***	0.2971***
	(0.0054)	(0.0043)
ln_goods_merchants (21)	0.0389***	0.1146***
	(0.0071)	(0.0063)
ln_service_merchants (22)	0.3714***	0.3686***
	(0.0075)	(0.0065)
ln_traffic (23)	-0.3411***	-0.2051***
	(0.0060)	(0.0050)
ln_administration (24)	0.1746***	0.1861***
	(0.0043)	(0.0033)
ln_regulatory_safety (25)	-0.0975***	-0.0514***
	(0.0097)	(0.0084)
ln_writing_art (26)	0.1741***	0.1966***
	(0.0144)	(0.0139)
ln_healthcare (27)	-0.1575***	-0.1050***
	(0.0070)	(0.0068)
ln_social_education_science (28)	0.1381***	0.1966***
	(0.0079)	(0.0075)
ln_age	1.3427***	1.1820***
	(0.0050)	(0.0053)
lvl_of_performance	0.1351***	0.1240***
	(0.0018)	(0.0020)
ln_formerjobs	0.0233***	0.0091***
	(0.0006)	(0.0006)
days_unemployed	-0.0002***	-0.0004***
	0.0000	0.0000
ln_experience	0.0809***	0.0489***
	(0.0003)	(0.0004)
employment_change	0.0014**	-0.0009
	(0.0005)	(0.0005)
1.vocTrain	0.0000	0.0000
	(.)	(.)
2.vocTrain	0.0510***	0.0306***
	(0.0015)	(0.0017)
3.vocTrain	-0.0407***	-0.0395***
	(0.0044)	(0.0053)
4.vocTrain	0.1214***	0.0945***
	(0.0027)	(0.0031)
5.vocTrain	0.2732***	0.2143***
	(0.0028)	(0.0032)
1.KldB88	0.0000	0.0000
	(.)	(.)
2.KldB88	0.1694***	0.1853***

Dependent variable: log wage	Occupation specific co-efficients of log tech age *entire sample* (1)	Occupation specific co-efficients of log tech age *entire sample*, lagged technological age (16)
	(0.0044)	(0.0049)
3.KldB88	0.1328***	0.1355***
	(0.0056)	(0.0063)
4.KldB88	0.1097***	0.1061***
	(0.0037)	(0.0041)
5.KldB88	0.1230***	0.1225***
	(0.0046)	(0.0049)
6.KldB88	0.1288***	0.1402***
	(0.0054)	(0.0059)
7.KldB88	0.0949***	0.1051***
	(0.0033)	(0.0038)
8.KldB88	0.0360***	0.0577***
	(0.0032)	(0.0036)
9.KldB88	0.0046	0.0182***
	(0.0037)	(0.0041)
10.KldB88	0.1132***	0.1146***
	(0.0034)	(0.0039)
11.KldB88	0.0318***	0.0494***
	(0.0044)	(0.0050)
12.KldB88	0.0458***	0.0578***
	(0.0037)	(0.0043)
13.KldB88	0.1560***	0.1656***
	(0.0032)	(0.0037)
14.KldB88	0.1359***	0.1467***
	(0.0041)	(0.0046)
15.KldB88	0.0577***	0.0862***
	(0.0042)	(0.0046)
16.KldB88	0.0745***	0.0995***
	(0.0042)	(0.0047)
17.KldB88	0.0893***	0.0836***
	(0.0036)	(0.0040)
18.KldB88	0.1337***	0.1390***
	(0.0038)	(0.0042)
19.KldB88	-0.0373***	0.0014
	(0.0056)	(0.0054)
20.KldB88	0.0088*	0.0343***
	(0.0039)	(0.0041)
21.KldB88	0.0634***	0.0717***
	(0.0036)	(0.0040)
22.KldB88	0.0558***	0.0725***
	(0.0051)	(0.0051)
23.KldB88	0.0916***	0.0917***
	(0.0031)	(0.0036)
24.KldB88	0.0447***	0.0622***

Dependent variable: log wage	Occupation specific co-efficients of log tech age *entire sample* (1)	Occupation specific co-efficients of log tech age *entire sample*, lagged technological age (16)
	(0.0037)	(0.0039)
25.KldB88	0.0688***	0.0636***
	(0.0047)	(0.0047)
26.KldB88	0.0737***	0.0772***
	(0.0071)	(0.0074)
27.KldB88	0.1845***	0.1775***
	(0.0049)	(0.0056)
28.KldB88	0.0288***	0.0314***
	(0.0049)	(0.0054)
1.industry	0.0000	0.0000
	(.)	(.)
2.industry	0.0832***	0.0721***
	(0.0030)	(0.0032)
3.industry	0.0815***	0.0747***
	(0.0027)	(0.0030)
4.industry	0.1156***	0.1016***
	(0.0028)	(0.0031)
5.industry	0.0328***	0.0298***
	(0.0027)	(0.0030)
6.industry	-0.2013***	-0.1994***
	(0.0040)	(0.0047)
7.industry	0.0178***	0.0185***
	(0.0027)	(0.0029)
8.industry	-0.0188***	-0.0170***
	(0.0027)	(0.0029)
9.industry	-0.0306***	-0.0376***
	(0.0029)	(0.0032)
10.industry	-0.0496***	-0.0433***
	(0.0027)	(0.0030)
11.industry	(0.0040)	(0.0043)
	(0.0031)	(0.0034)
12.industry	-0.0144***	-0.0222***
	(0.0031)	(0.0034)
13.industry	0.0432***	0.0250***
	(0.0029)	(0.0032)
1.state	0.0000	0.0000
	(.)	(.)
2.state	0.0670***	0.0609***
	(0.0033)	(0.0035)
3.state	-0.0107**	-0.0121**
	(0.0037)	(0.0039)
4.state	0.0292***	0.0269***
	(0.0051)	(0.0054)
5.state	0.0299***	0.0266***

Dependent variable: log wage	Occupation specific co-efficients of log tech age *entire sample* (1)	Occupation specific co-efficients of log tech age *entire sample*, lagged technological age (16)
	(0.0037)	(0.0039)
6.state	0.0607***	0.0526***
	(0.0039)	(0.0041)
7.state	-0.0103*	-0.0132**
	(0.0043)	(0.0046)
8.state	0.0468***	0.0379***
	(0.0039)	(0.0041)
9.state	0.0422***	0.0340***
	(0.0039)	(0.0041)
10.state	-0.0315***	-0.0313***
	(0.0066)	(0.0069)
11.state	-0.0289***	-0.0317***
	(0.0043)	(0.0046)
12.state	-0.1534***	-0.1505***
	(0.0046)	(0.0050)
13.state	-0.1906***	-0.1847***
	(0.0054)	(0.0059)
14.state	-0.1928***	-0.1866***
	(0.0045)	(0.0049)
15.state	-0.1909***	-0.1846***
	(0.0047)	(0.0050)
16.state	-0.1931***	-0.1885***
	(0.0050)	(0.0054)
1979.year	0.0000	
	(.)	
1980.year	-0.0158***	0.0000
	(0.0005)	(.)
1981.year	-0.0231***	0.0058***
	(0.0007)	(0.0005)
1982.year	-0.0454***	-0.0064***
	(0.0008)	(0.0006)
1983.year	-0.0677***	-0.0195***
	(0.0009)	(0.0007)
1984.year	-0.0657***	-0.0077***
	(0.0010)	(0.0008)
1985.year	-0.0709***	-0.0052***
	(0.0011)	(0.0009)
1986.year	-0.0790***	-0.0066***
	(0.0012)	(0.0011)
1987.year	-0.0851***	-0.0076***
	(0.0013)	(0.0012)
1988.year	-0.0991***	-0.0155***
	(0.0014)	(0.0013)
1989.year	-0.1003***	-0.0112***

Dependent variable: log wage	Occupation specific co-efficients of log tech age *entire sample* (1)	Occupation specific co-efficients of log tech age *entire sample*, lagged technological age (16)
	(0.0015)	(0.0014)
1990.year	-0.0789***	0.0156***
	(0.0017)	(0.0015)
1991.year	-0.0543***	0.0450***
	(0.0018)	(0.0016)
1992.year	-0.0500***	0.0664***
	(0.0019)	(0.0018)
1993.year	-0.0468***	0.0575***
	(0.0020)	(0.0019)
1994.year	-0.0614***	0.0508***
	(0.0021)	(0.0020)
1995.year	-0.0675***	0.0532***
	(0.0023)	(0.0022)
1996.year	-0.0904***	0.0389***
	(0.0024)	(0.0023)
1997.year	-0.1203***	0.0179***
	(0.0025)	(0.0024)
1998.year	-0.1513***	(0.0047)
	(0.0027)	(0.0025)
1999.year	-0.1653***	-0.0116***
	(0.0028)	(0.0027)
2000.year	-0.1786***	-0.0253***
	(0.0030)	(0.0028)
2001.year	-0.1851***	-0.0274***
	(0.0031)	(0.0029)
2002.year	-0.2003***	-0.0365***
	(0.0032)	(0.0031)
2003.year	-0.2230***	-0.0529***
	(0.0034)	(0.0032)
2004.year	-0.2509***	-0.0738***
	(0.0035)	(0.0034)
2005.year	-0.2782***	-0.0936***
	(0.0037)	(0.0035)
2006.year	-0.3012***	-0.1091***
	(0.0038)	(0.0036)
Constant	-1.0005***	-0.4347***
	(0.0167)	(0.0180)
N	11,012,285	9,603,524
R-sq	0.5218	0.5035

*Note: Dependent variable is log daily wage. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A14. Occupation change analysis full output tables

A14.i. Regression results *overall sample* non occupation specific technological age

Table A59: *Regression (17), the impact of technological age on the likelihood to change occupations, overall sample, non occupation specific technological age*

Dependent variable: occupation change in $t+1$	technological age
	(17)
techage	0.0127***
	(.0014)
age_sqared	0.0000***
	.0000
lvl_of_performance	-0.0148***
	(.0005)
ln_formerjobs	-0.0182***
	(.0002)
days_unemployed	-0.0000***
	.0000
experience	0.0060***
	.0000
employment_change	-0.0121***
	(.0005)
1.vocTrain	0
	(.)
2.vocTrain	-0.0998***
	(.0011)
3.vocTrain	-0.0742***
	(.0026)
4.vocTrain	-0.1466***
	(.0019)
5.vocTrain	-0.2140***
	(.0020)
1.industry	0
	(.)
2.industry	-0.0282***
	(.0025)
3.industry	-0.0318***
	(.0023)
4.industry	-0.0443***
	(.0023)
5.industry	-0.0115***
	(.0023)

6.industry	0.0104***
	(.0031)
7.industry	-0.0129***
	(.0023)
8.industry	-0.0022
	(.0022)
9.industry	-0.0293***
	(.0024)
10.industry	-0.0016
	(.0022)
11.industry	-0.0241***
	(.0024)
12.industry	-0.0359***
	(.0024)
13.industry	-0.0430***
	(.0024)
1.state	0
	(.)
2.state	-0.0113***
	(.0022)
3.state	0.0023
	(.0025)
4.state	-0.0049
	(.0034)
5.state	-0.0037
	(.0024)
6.state	-0.0067**
	(.0025)
7.state	0.0065*
	(.0029)
8.state	-0.0033
	(.0025)
9.state	-0.0022
	(.0025)
10.state	-0.0008
	(.0045)
11.state	-0.003
	(.0029)
12.state	0.0132***
	(.0034)
13.state	0.0133**
	(.0042)
14.state	0.0139***
	(.0033)
15.state	0.0177***
	(.0037)
16.state	0.0180***
	(.0038)
1.KldB88	0
	(.)

2.KldB88	0.009
	(.0046)
3.KldB88	0.0132*
	(.0058)
4.KldB88	-0.0070*
	(.0033)
5.KldB88	-0.0353***
	(.0039)
6.KldB88	0.0277***
	(.0055)
7.KldB88	-0.0056
	(.0031)
8.KldB88	-0.0245***
	(.0028)
9.KldB88	-0.0354***
	(.0032)
10.KldB88	0.0152***
	(.0031)
11.KldB88	0.0066
	(.0038)
12.KldB88	0
	(.0033)
13.KldB88	-0.0263***
	(.0029)
14.KldB88	0.0164***
	(.0039)
15.KldB88	-0.0168***
	(.0039)
16.KldB88	-0.0283***
	(.0041)
17.KldB88	0.0144***
	(.0032)
18.KldB88	-0.0109**
	(.0036)
19.KldB88	-0.1039***
	(.0034)
20.KldB88	-0.0672***
	(.0030)
21.KldB88	-0.0506***
	(.0029)
22.KldB88	-0.0962***
	(.0033)
23.KldB88	-0.0467***
	(.0028)
24.KldB88	-0.1065***
	(.0029)
25.KldB88	-0.0540***
	(.0033)
26.KldB88	-0.0832***
	(.0043)

27.KldB88	-0.1467***
	(.0035)
28.KldB88	-0.0971***
	(.0035)
1979.year	0
	(.)
1980.year	-0.0067***
	(.0006)
1981.year	-0.0189***
	(.0007)
1982.year	-0.0323***
	(.0007)
1983.year	-0.0424***
	(.0008)
1984.year	-0.0492***
	(.0008)
1985.year	-0.0543***
	(.0009)
1986.year	-0.0591***
	(.0010)
1987.year	-0.0672***
	(.0011)
1988.year	-0.0743***
	(.0012)
1989.year	-0.0770***
	(.0013)
1990.year	-0.0826***
	(.0014)
1991.year	-0.0897***
	(.0015)
1992.year	-0.0899***
	(.0016)
1993.year	-0.1030***
	(.0017)
1994.year	-0.1140***
	(.0018)
1995.year	-0.1229***
	(.0019)
1996.year	-0.1285***
	(.0020)
1997.year	-0.1330***
	(.0021)
1998.year	-0.1404***
	(.0022)
1999.year	-0.1454***
	(.0023)
2000.year	-0.1493***
	(.0024)
2001.year	-0.1582***
	(.0025)

2002.year	-0.1703***
	(.0026)
2003.year	-0.1803***
	(.0027)
2004.year	-0.1895***
	(.0029)
2005.year	-0.2006***
	(.0030)
2006.year	-0.2088***
	(.0031)
Constant	0.3661***
	(.0038)
N	11,030,551
R-sq	0.0507

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level. ln_techage is not interacted with occupation dummies.*

A14.ii. Regression results *overall sample* - full output table

Table A60: *Regression (5), the impact of technological age on the likelihood to change occupations, overall sample, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)
agriculture_fishing (1)	0.0068
	(.0061)
miners_stone_workers (2)	0.0879***
	(.0126)
ceramic_glas (3)	-0.0694***
	(.0153)
chemistry_synthetic_workers (4)	-0.0739***
	(.0041)
paper_print (5)	-0.0369***
	(.0054)
woodworking (6)	0.1704
	(.1014)
metal_works (7)	-0.0138***
	(.0035)
mechanics (8)	0.0472***
	(.0023)
electricians (9)	0.0598***
	(.0032)
assembly (10)	-0.0591***
	(.0051)
textile_clothing_leather_fur (11)	0.1171***
	(.0116)
food (12)	0.0950***
	(.0074)
construction (13)	0.2608***
	(.0088)
interior_construction (14)	0.0506***
	(.0101)
carpenter (15)	0.0980***
	(.0073)
painter (16)	0.1099***
	(.0080)
product_testing (17)	-0.0989***
	(.0057)
machinist (18)	0.0104
	(.0060)
engineer_math_chem (19)	0.0247***
	(.0029)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)
technical_specilaist (20)	0.0418***
	(.0023)
goods_merchants (21)	0.0155***
	(.0029)
service_merchants (22)	-0.0063*
	(.0027)
traffic (23)	-0.0163***
	(.0033)
administration (24)	0.0194***
	(.0016)
regulatory_safety (25)	-0.0561***
	(.0049)
writing_art (26)	0.0255***
	(.0056)
healthcare (27)	0.0520***
	(.0020)
social_education_science (28)	0.0251***
	(.0028)
age_sqared	0.0000***
	.0000
lvl_of_performance	-0.0152***
	(.0005)
ln_formerjobs	-0.0184***
	(.0002)
days_unemployed	-0.0000***
	.0000
experience	0.0057***
	.0000
employment_change	-0.0099***
	(.0005)
1.vocTrain	0
	(.)
2.vocTrain	-0.0975***
	(.0011)
3.vocTrain	-0.0728***
	(.0026)
4.vocTrain	-0.1450***
	(.0019)
5.vocTrain	-0.2126***
	(.0020)
1.industry	0
	(.)
2.industry	-0.0280***
	(.0025)
3.industry	-0.0316***
	(.0023)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)
4.industry	-0.0443***
	(.0023)
5.industry	-0.0114***
	(.0023)
6.industry	0.0106***
	(.0031)
7.industry	-0.0121***
	(.0023)
8.industry	-0.0021
	(.0022)
9.industry	-0.0283***
	(.0024)
10.industry	-0.0015
	(.0022)
11.industry	-0.0243***
	(.0024)
12.industry	-0.0363***
	(.0024)
13.industry	-0.0433***
	(.0024)
1.state	0
	(.)
2.state	-0.0114***
	(.0022)
3.state	0.0022
	(.0025)
4.state	-0.0051
	(.0034)
5.state	-0.0037
	(.0024)
6.state	-0.0066**
	(.0025)
7.state	0.0063*
	(.0029)
8.state	-0.0033
	(.0025)
9.state	-0.0023
	(.0025)
10.state	-0.0005
	(.0045)
11.state	-0.0028
	(.0029)
12.state	0.0134***
	(.0034)
13.state	0.0135**
	(.0042)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)
14.state	0.0141***
	(.0033)
15.state	0.0179***
	(.0037)
16.state	0.0182***
	(.0038)
1.KldB88	0
	(.)
2.KldB88	0.0034
	(.0048)
3.KldB88	0.0185**
	(.0061)
4.KldB88	0.0097**
	(.0035)
5.KldB88	-0.0255***
	(.0042)
6.KldB88	0.0280***
	(.0056)
7.KldB88	-0.0037
	(.0032)
8.KldB88	-0.0309***
	(.0030)
9.KldB88	-0.0472***
	(.0033)
10.KldB88	0.0217***
	(.0033)
11.KldB88	0.0027
	(.0039)
12.KldB88	-0.0051
	(.0034)
13.KldB88	-0.0356***
	(.0031)
14.KldB88	0.0119**
	(.0041)
15.KldB88	-0.0267***
	(.0041)
16.KldB88	-0.0365***
	(.0042)
17.KldB88	0.0336***
	(.0035)
18.KldB88	-0.0113**
	(.0039)
19.KldB88	-0.1131***
	(.0038)
20.KldB88	-0.0838***
	(.0033)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)
21.KldB88	-0.0526***
	(.0031)
22.KldB88	-0.0875***
	(.0036)
23.KldB88	-0.0439***
	(.0029)
24.KldB88	-0.1117***
	(.0030)
25.KldB88	-0.0253***
	(.0041)
26.KldB88	-0.0891***
	(.0050)
27.KldB88	-0.1598***
	(.0036)
28.KldB88	-0.1014***
	(.0037)
1979.year	0
	(.)
1980.year	-0.0069***
	(.0006)
1981.year	-0.0191***
	(.0007)
1982.year	-0.0326***
	(.0007)
1983.year	-0.0427***
	(.0008)
1984.year	-0.0495***
	(.0008)
1985.year	-0.0548***
	(.0009)
1986.year	-0.0600***
	(.0010)
1987.year	-0.0681***
	(.0011)
1988.year	-0.0754***
	(.0012)
1989.year	-0.0782***
	(.0013)
1990.year	-0.0840***
	(.0014)
1991.year	-0.0914***
	(.0015)
1992.year	-0.0917***
	(.0016)
1993.year	-0.1048***
	(.0017)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)
1994.year	-0.1160***
	(.0018)
1995.year	-0.1252***
	(.0019)
1996.year	-0.1311***
	(.0020)
1997.year	-0.1358***
	(.0021)
1998.year	-0.1434***
	(.0022)
1999.year	-0.1486***
	(.0023)
2000.year	-0.1531***
	(.0024)
2001.year	-0.1625***
	(.0025)
2002.year	-0.1749***
	(.0026)
2003.year	-0.1851***
	(.0028)
2004.year	-0.1946***
	(.0029)
2005.year	-0.2059***
	(.0030)
2006.year	-0.2144***
	(.0031)
Constant	0.3665***
	(.0039)
N	11,030,551
R-sq	0.0515

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A14.iii. Regression results *subsample 79*, *subsample 90* and *subsample 00* - full output tables

Table A61: *Regressions (5), (6), (7) and (8), the impact technological age on the likelihood to change occupations, overall sample, subsample 79, subsample 90 and subsample 00, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
agriculture_fishing (1)	0.0068	2.1658***	0.5032***	-0.0610***
	(.0061)	(.1403)	(.0410)	(.0127)
miners_stone_workers (2)	0.0879***	1.0046***	1.0756***	0.0167
	(.0126)	(.2947)	(.1842)	(.0225)
ceramic_glas (3)	-0.0694***	1.9840***	0.1034	-0.0906*
	(.0153)	(.3556)	(.0543)	(.0440)
chemistry_synthetic_workers (4)	-0.0739***	0.2275***	-0.0173	-0.0658***
	(.0041)	(.0370)	(.0217)	(.0094)
paper_print (5)	-0.0369***	0.1342***	0.1322***	-0.0906***
	(.0054)	(.0336)	(.0364)	(.0137)
woodworking (6)	0.1704	2.4964***	0.6451***	-0.1832
	(.1014)	(.3505)	(.1767)	(.1687)
metal_works (7)	-0.0138***	1.3648***	0.7878***	-0.0230***
	(.0035)	(.0680)	(.0679)	(.0063)
mechanics (8)	0.0472***	1.0657***	0.2961***	0.0211***
	(.0023)	(.0395)	(.0181)	(.0057)
electricians (9)	0.0598***	0.4146***	0.2733***	-0.0076
	(.0032)	(.0240)	(.0160)	(.0104)
assembly (10)	-0.0591***	1.0787***	0.3605***	-0.0478***
	(.0051)	(.0728)	(.0478)	(.0096)
textile_clothing_leather_fur (11)	0.1171***	2.9615***	0.7649***	0.0266
	(.0116)	(.1737)	(.0969)	(.0211)
food (12)	0.0950***	2.9712***	0.8365***	0.0340*
	(.0074)	(.1483)	(.0517)	(.0156)
construction (13)	0.2608***	2.3684***	0.9925***	0.1359***
	(.0088)	(.1482)	(.0624)	(.0193)
interior_construction (14)	0.0506***	1.5288***	0.5551***	0.0400*
	(.0101)	(.1775)	(.0763)	(.0201)
carpenter (15)	0.0980***	1.7194***	0.4862***	0.0436**
	(.0073)	(.1184)	(.0482)	(.0168)
painter (16)	0.1099***	2.3965***	0.7380***	0.0760***
	(.0080)	(.1831)	(.0985)	(.0156)
product_testing (17)	-0.0989***	0.4844***	0.042	-0.1040***
	(.0057)	(.0425)	(.0378)	(.0129)
machinist (18)	0.0104	0.7535***	0.4457***	-0.0038
	(.0060)	(.0779)	(.0556)	(.0119)
engineer_math_chem (19)	0.0247***	0.1018***	0.0927***	-0.0970**

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
	(.0029)	(.0074)	(.0115)	(.0310)
technical_specilaist (20)	0.0418***	0.1856***	0.1185***	-0.0797***
	(.0023)	(.0086)	(.0084)	(.0178)
goods_merchants (21)	0.0155***	0.6156***	0.1563***	-0.0612***
	(.0029)	(.0188)	(.0124)	(.0102)
service_merchants (22)	-0.0063*	0.0594***	0.0102	-0.1770***
	(.0027)	(.0064)	(.0131)	(.0237)
traffic (23)	-0.0163***	0.8995***	0.2328***	-0.0458***
	(.0033)	(.0455)	(.0249)	(.0082)
administration (24)	0.0194***	0.0942***	0.0391***	-0.1193***
	(.0016)	(.0051)	(.0068)	(.0167)
regulatory_safety (25)	-0.0561***	0.2376***	-0.0219	-0.1330***
	(.0049)	(.0283)	(.0144)	(.0203)
writing_art (26)	0.0255***	0.2545***	0.1455***	-0.0425
	(.0056)	(.0211)	(.0178)	(.0266)
healthcare (27)	0.0520***	0.3905***	0.0864***	-0.0443***
	(.0020)	(.0197)	(.0063)	(.0105)
social_education_science (28)	0.0251***	0.3550***	0.0955***	-0.0691***
	(.0028)	(.0252)	(.0100)	(.0107)
age_sqared	0.0000***	-0.0001***	-0.0001***	0.0000***
	.0000	.0000	.0000	.0000
lvl_of_performance	-0.0152***	-0.0141***	-0.0150***	-0.0137***
	(.0005)	(.0013)	(.0011)	(.0016)
ln_formerjobs	-0.0184***	-0.0196***	-0.0292***	-0.0383***
	(.0002)	(.0004)	(.0004)	(.0006)
days_unemployed	-0.0000***	0	-0.0000***	-0.0000***
	.0000	.0000	.0000	.0000
experience	0.0057***	0.0251***	0.0158***	0.0171***
	.0000	(.0002)	(.0001)	(.0002)
employment_change	-0.0099***	-0.0033***	-0.0117***	-0.0006
	(.0005)	(.0009)	(.0007)	(.0012)
1.vocTrain	0	0	0	0
	(.)	(.)	(.)	(.)
2.vocTrain	-0.0975***	-0.0763***	-0.1143***	-0.1143***
	(.0011)	(.0020)	(.0026)	(.0039)
3.vocTrain	-0.0728***	-0.0551***	-0.0987***	-0.1086***
	(.0026)	(.0058)	(.0057)	(.0074)
4.vocTrain	-0.1450***	-0.1355***	-0.1752***	-0.1811***
	(.0019)	(.0043)	(.0040)	(.0056)
5.vocTrain	-0.2126***	-0.1886***	-0.2430***	-0.2354***
	(.0020)	(.0044)	(.0041)	(.0059)
1.industry	0	0	0	0
	(.)	(.)	(.)	(.)
2.industry	-0.0280***	-0.0123*	-0.0518***	-0.0481***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
	(.0025)	(.0055)	(.0047)	(.0069)
3.industry	-0.0316***	-0.0190***	-0.0513***	-0.0574***
	(.0023)	(.0051)	(.0043)	(.0065)
4.industry	-0.0443***	-0.0433***	-0.0598***	-0.0579***
	(.0023)	(.0052)	(.0044)	(.0066)
5.industry	-0.0114***	0.0061	-0.0378***	-0.0254***
	(.0023)	(.0051)	(.0043)	(.0065)
6.industry	0.0106***	0.0338***	-0.0183**	0.0171*
	(.0031)	(.0067)	(.0059)	(.0085)
7.industry	-0.0121***	0	-0.0454***	-0.0087
	(.0023)	(.0051)	(.0042)	(.0064)
8.industry	-0.0021	0.0216***	-0.0316***	-0.0154*
	(.0022)	(.0049)	(.0041)	(.0061)
9.industry	-0.0283***	-0.0239***	-0.0500***	-0.0392***
	(.0024)	(.0054)	(.0045)	(.0065)
10.industry	-0.0015	0.0051	-0.0271***	0.0057
	(.0022)	(.0051)	(.0041)	(.0061)
11.industry	-0.0243***	-0.0266***	-0.0466***	-0.0064
	(.0024)	(.0055)	(.0045)	(.0066)
12.industry	-0.0363***	-0.0399***	-0.0598***	-0.0068
	(.0024)	(.0055)	(.0045)	(.0067)
13.industry	-0.0433***	-0.0479***	-0.0571***	-0.0410***
	(.0024)	(.0053)	(.0044)	(.0069)
1.state	0	0	0	0
	(.)	(.)	(.)	(.)
2.state	-0.0114***	-0.0156***	-0.0073	0.0021
	(.0022)	(.0047)	(.0044)	(.0059)
3.state	0.0022	0.0028	-0.005	0.0081
	(.0025)	(.0053)	(.0049)	(.0064)
4.state	-0.0051	-0.0109	-0.0192**	0.0119
	(.0034)	(.0071)	(.0071)	(.0093)
5.state	-0.0037	-0.0056	-0.0057	0.0053
	(.0024)	(.0052)	(.0048)	(.0062)
6.state	-0.0066**	-0.0053	-0.0086	-0.0023
	(.0025)	(.0056)	(.0051)	(.0066)
7.state	0.0063*	0.0023	0.0112	0.0117
	(.0029)	(.0062)	(.0058)	(.0075)
8.state	-0.0033	-0.0084	-0.0075	0.0024
	(.0025)	(.0056)	(.0051)	(.0066)
9.state	-0.0023	-0.0046	-0.0019	0.0019
	(.0025)	(.0056)	(.0051)	(.0065)
10.state	-0.0005	-0.0095	0.0073	0.0319**
	(.0045)	(.0095)	(.0090)	(.0115)
11.state	-0.0028	-0.0052	0.0011	0.0160*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
	(.0029)	(.0073)	(.0056)	(.0071)
12.state	0.0134***		0.0121*	0.0307***
	(.0034)		(.0061)	(.0076)
13.state	0.0135**		0.0097	0.0346***
	(.0042)		(.0072)	(.0086)
14.state	0.0141***		0.0123*	0.0270***
	(.0033)		(.0059)	(.0075)
15.state	0.0179***		0.0131*	0.0356***
	(.0037)		(.0064)	(.0080)
16.state	0.0182***		0.0147*	0.0225**
	(.0038)		(.0066)	(.0083)
1.KldB88	0	0	0	0
	(.)	(.)	(.)	(.)
2.KldB88	0.0034	-0.0407***	0.0676***	0.0302
	(.0048)	(.0093)	(.0112)	(.0172)
3.KldB88	0.0185**	0.0126	0.0747***	0.0026
	(.0061)	(.0116)	(.0127)	(.0247)
4.KldB88	0.0097**	-0.0496***	0.0607***	-0.001
	(.0035)	(.0077)	(.0078)	(.0119)
5.KldB88	-0.0255***	-0.0929***	-0.0203	-0.0066
	(.0042)	(.0088)	(.0117)	(.0149)
6.KldB88	0.0280***	0.0374***	0.0844***	0.0561*
	(.0056)	(.0109)	(.0111)	(.0222)
7.KldB88	-0.0037	-0.0475***	0.0216**	-0.0246*
	(.0032)	(.0070)	(.0076)	(.0108)
8.KldB88	-0.0309***	-0.0635***	-0.009	-0.0561***
	(.0030)	(.0067)	(.0061)	(.0093)
9.KldB88	-0.0472***	-0.1104***	-0.0567***	-0.0359**
	(.0033)	(.0076)	(.0076)	(.0113)
10.KldB88	0.0217***	-0.0329***	0.0587***	0.0184
	(.0033)	(.0072)	(.0068)	(.0105)
11.KldB88	0.0027	-0.0039	0.0887***	0.0066
	(.0039)	(.0080)	(.0084)	(.0160)
12.KldB88	-0.0051	0.0084	0.0469***	-0.0646***
	(.0034)	(.0075)	(.0069)	(.0109)
13.KldB88	-0.0356***	-0.0409***	-0.0084	-0.0453***
	(.0031)	(.0068)	(.0061)	(.0097)
14.KldB88	0.0119**	0.0106	0.0325***	-0.0102
	(.0041)	(.0087)	(.0088)	(.0128)
15.KldB88	-0.0267***	-0.0490***	-0.0196*	-0.0321*
	(.0041)	(.0090)	(.0089)	(.0134)
16.KldB88	-0.0365***	-0.0543***	-0.0096	-0.0749***
	(.0042)	(.0090)	(.0089)	(.0131)
17.KldB88	0.0336***	-0.0327***	0.0651***	0.0345**

Dependent variable: occupation change in $t + 1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
	(.0035)	(.0074)	(.0088)	(.0116)
18.KldB88	-0.0113**	-0.0799***	0.0159	-0.0077
	(.0039)	(.0087)	(.0092)	(.0131)
19.KldB88	-0.1131***	-0.2351***	-0.1210***	-0.014
	(.0038)	(.0088)	(.0105)	(.0256)
20.KldB88	-0.0838***	-0.1896***	-0.0885***	-0.0151
	(.0033)	(.0074)	(.0074)	(.0159)
21.KldB88	-0.0526***	-0.1235***	-0.0522***	-0.0485***
	(.0031)	(.0069)	(.0064)	(.0101)
22.KldB88	-0.0875***	-0.1930***	-0.0759***	0.0482*
	(.0036)	(.0083)	(.0110)	(.0190)
23.KldB88	-0.0439***	-0.1063***	-0.0215***	-0.0671***
	(.0029)	(.0065)	(.0060)	(.0091)
24.KldB88	-0.1117***	-0.2027***	-0.0993***	-0.0348*
	(.0030)	(.0070)	(.0071)	(.0149)
25.KldB88	-0.0253***	-0.1038***	0.008	-0.0152
	(.0041)	(.0089)	(.0089)	(.0166)
26.KldB88	-0.0891***	-0.1621***	-0.0959***	-0.0479*
	(.0050)	(.0107)	(.0117)	(.0199)
27.KldB88	-0.1598***	-0.2171***	-0.1521***	-0.1299***
	(.0036)	(.0085)	(.0076)	(.0126)
28.KldB88	-0.1014***	-0.1884***	-0.0991***	-0.0578***
	(.0037)	(.0088)	(.0078)	(.0122)
1979.year	0	0		
	(.)	(.)		
1980.year	-0.0069***	-0.0165***		
	(.0006)	(.0007)		
1981.year	-0.0191***	-0.0383***		
	(.0007)	(.0009)		
1982.year	-0.0326***	-0.0612***		
	(.0007)	(.0012)		
1983.year	-0.0427***	-0.0815***		
	(.0008)	(.0015)		
1984.year	-0.0495***	-0.0984***		
	(.0008)	(.0018)		
1985.year	-0.0548***	-0.1146***		
	(.0009)	(.0021)		
1986.year	-0.0600***	-0.1308***		
	(.0010)	(.0024)		
1987.year	-0.0681***	-0.1521***		
	(.0011)	(.0027)		
1988.year	-0.0754***	-0.1726***		
	(.0012)	(.0031)		
1989.year	-0.0782***	-0.1878***		

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of tech age *overall sample* (5)	Occupation specific coefficients of tech age *subsample 79* (6)	Occupation specific coefficients of tech age *subsample 90* (7)	Occupation specific coefficients of tech age *subsample 00* (8)
	(.0013)	(.0034)		
1990.year	-0.0840***		0	
	(.0014)		(.)	
1991.year	-0.0914***		-0.0075***	
	(.0015)		(.0006)	
1992.year	-0.0917***		-0.0117***	
	(.0016)		(.0009)	
1993.year	-0.1048***		-0.0255***	
	(.0017)		(.0012)	
1994.year	-0.1160***		-0.0386***	
	(.0018)		(.0015)	
1995.year	-0.1252***		-0.0506***	
	(.0019)		(.0018)	
1996.year	-0.1311***		-0.0592***	
	(.0020)		(.0021)	
1997.year	-0.1358***		-0.0673***	
	(.0021)		(.0025)	
1998.year	-0.1434***		-0.0777***	
	(.0022)		(.0028)	
1999.year	-0.1486***		-0.0848***	
	(.0023)		(.0031)	
2000.year	-0.1531***			0
	(.0024)			(.)
2001.year	-0.1625***			-0.0123***
	(.0025)			(.0007)
2002.year	-0.1749***			-0.0283***
	(.0026)			(.0011)
2003.year	-0.1851***			-0.0426***
	(.0028)			(.0016)
2004.year	-0.1946***			-0.0572***
	(.0029)			(.0021)
2005.year	-0.2059***			-0.0737***
	(.0030)			(.0026)
2006.year	-0.2144***			-0.0877***
	(.0031)			(.0031)
Constant	0.3665***	0.4599***	0.3840***	0.2606***
	(.0039)	(.0090)	(.0085)	(.0134)
N	11,030,551	3,839,340	4,37,1323	2,819,888
R-sq	0.0515	0.0496	0.0501	0.0701

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A15. Robustness checks occupation change analysis full output table

A15.i. Regression *overall sample* using *KldB2010* - full output table

Table A62: *Regression (18), the impact of technological age on the likelihood to change occupations, overall sample, KldB2010, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
agriculture (11)	-0.0263**
	(0.0093)
gardening (12)	0.0199
	(0.0113)
raw_material_prod (21)	0.0379***
	(0.0102)
plastic_wood_process (22)	0.0062
	(0.0043)
paper_process (23)	-0.0129**
	(0.0046)
metal_making (24)	0.0041
	(0.0027)
machine_car_build (25)	0.0182***
	(0.0022)
electrical_engineer (26)	0.0185***
	(0.0038)
tech_research_construction (27)	0.0144***
	(0.0027)
textile_process (28)	0.1041***
	(0.0108)
food_process (29)	0.0370***
	(0.0078)
architecture (31)	0.0430***
	(0.0046)
construction (32)	0.2417***
	(0.0109)
interior_constr (33)	0.1277***
	(0.0099)
build_engineer (34)	0.0639***
	(0.0054)
math_bio_chem (41)	-0.0279***
	(0.0036)
geo (42)	0.0477**

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
	(0.0184)
IT (43)	-0.0680***
	(0.0074)
logistics (51)	-0.0719***
	(0.0036)
drivers (52)	0.0287***
	(0.0061)
safety (53)	-0.0476***
	(0.0053)
cleaning_service (54)	0.1103***
	(0.0320)
purchasing_sales (61)	0.0046
	(0.0032)
retail (62)	-0.0223***
	(0.0041)
tourism (63)	0.0272**
	(0.0089)
management (71)	0.0208***
	(0.0016)
finance (72)	-0.0026
	(0.0026)
law (73)	-0.0306***
	(0.0071)
medical (81)	0.0401***
	(0.0021)
wellness (82)	0.0940***
	(0.0080)
education (83)	0.0017
	(0.0033)
teaching (84)	-0.0265***
	(0.0046)
social_science (91)	-0.0299**
	(0.0109)
marketing (92)	-0.0069
	(0.0078)
craftwork (93)	0.0391**
	(0.0123)
entertainment (94)	0.0965***
	(0.0147)
age_squared	0
	0.0000
lvl_of_performance	-0.0215***
	(0.0006)
formerjobs	-0.0202***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
	(0.0002)
days_unemployed	0.0000***
	0.0000
experience	0.0061***
	0.0000
1.vocTrain	0
	(.)
2.vocTrain	-0.0920***
	(0.0012)
3.vocTrain	-0.0572***
	(0.0029)
4.vocTrain	-0.1395***
	(0.0021)
5.vocTrain	-0.2142***
	(0.0021)
1.industry	0
	(.)
2.industry	-0.0275***
	(0.0027)
3.industry	-0.0311***
	(0.0026)
4.industry	-0.0394***
	(0.0026)
5.industry	-0.0091***
	(0.0026)
6.industry	0.0416***
	(0.0032)
7.industry	-0.0022
	(0.0026)
8.industry	0.0007
	(0.0025)
9.industry	-0.0189***
	(0.0027)
10.industry	0.0061*
	(0.0025)
11.industry	-0.0157***
	(0.0027)
12.industry	-0.0345***
	(0.0027)
13.industry	-0.0466***
	(0.0027)
1.state	0
	(.)
2.state	-0.0139***

Dependent variable: occupation change in $t + 1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
	(0.0025)
3.state	0.0028
	(0.0027)
4.state	-0.0058
	(0.0038)
5.state	-0.0069*
	(0.0027)
6.state	-0.0128***
	(0.0028)
7.state	0.0023
	(0.0032)
8.state	-0.0068*
	(0.0028)
9.state	-0.0063*
	(0.0028)
10.state	-0.0055
	(0.0049)
11.state	-0.0018
	(0.0032)
12.state	0.0111**
	(0.0038)
13.state	0.0123**
	(0.0048)
14.state	0.0085*
	(0.0037)
15.state	0.0164***
	(0.0041)
16.state	0.0113**
	(0.0043)
11.KldB2010	0
	(.)
12.KldB2010	-0.0151**
	(0.0059)
21.KldB2010	-0.0434***
	(0.0060)
22.KldB2010	-0.0522***
	(0.0052)
23.KldB2010	-0.0827***
	(0.0057)
24.KldB2010	-0.0581***
	(0.0050)
25.KldB2010	-0.0743***
	(0.0050)
26.KldB2010	-0.0964***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
	(0.0053)
27.KldB2010	-0.0915***
	(0.0053)
28.KldB2010	-0.0430***
	(0.0056)
29.KldB2010	-0.0487***
	(0.0053)
31.KldB2010	-0.1222***
	(0.0066)
32.KldB2010	-0.0699***
	(0.0051)
33.KldB2010	-0.0484***
	(0.0056)
34.KldB2010	-0.0667***
	(0.0054)
41.KldB2010	-0.0676***
	(0.0055)
42.KldB2010	-0.2362***
	(0.0295)
43.KldB2010	-0.0759***
	(0.0075)
51.KldB2010	-0.0344***
	(0.0051)
52.KldB2010	-0.1105***
	(0.0051)
53.KldB2010	-0.0668***
	(0.0061)
54.KldB2010	-0.0452***
	(0.0054)
61.KldB2010	-0.0835***
	(0.0054)
62.KldB2010	-0.0555***
	(0.0051)
63.KldB2010	-0.0839***
	(0.0057)
71.KldB2010	-0.1391***
	(0.0050)
72.KldB2010	-0.1337***
	(0.0054)
73.KldB2010	-0.0686***
	(0.0075)
81.KldB2010	-0.1861***
	(0.0055)
82.KldB2010	-0.0739***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
	(0.0070)
83.KldB2010	-0.0955***
	(0.0055)
84.KldB2010	-0.0871***
	(0.0065)
91.KldB2010	-0.0421***
	(0.0090)
92.KldB2010	-0.0993***
	(0.0081)
93.KldB2010	-0.0422***
	(0.0076)
94.KldB2010	-0.1086***
	(0.0096)
1979.year	0
	(.)
1980.year	-0.0064***
	(0.0006)
1981.year	-0.0208***
	(0.0007)
1982.year	-0.0318***
	(0.0007)
1983.year	-0.0395***
	(0.0008)
1984.year	-0.0447***
	(0.0009)
1985.year	-0.0499***
	(0.0009)
1986.year	-0.0534***
	(0.0010)
1987.year	-0.0612***
	(0.0011)
1988.year	-0.0645***
	(0.0012)
1989.year	-0.0676***
	(0.0013)
1990.year	-0.0724***
	(0.0014)
1991.year	-0.0779***
	(0.0015)
1992.year	-0.0789***
	(0.0016)
1993.year	-0.0904***
	(0.0017)
1994.year	-0.0984***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)
	(0.0018)
1995.year	-0.1042***
	(0.0019)
1996.year	-0.1127***
	(0.0020)
1997.year	-0.1126***
	(0.0021)
1998.year	-0.1157***
	(0.0023)
1999.year	-0.1192***
	(0.0024)
2000.year	-0.1237***
	(0.0025)
2001.year	-0.1315***
	(0.0026)
2002.year	-0.1424***
	(0.0027)
2003.year	-0.1507***
	(0.0028)
2004.year	-0.1562***
	(0.0030)
2005.year	-0.1641***
	(0.0031)
2006.year	-0.1675***
	(0.0032)
employment_change	-0.0101***
	(0.0005)
_cons	0.4292***
	(0.0057)
N	10,870,916
R-sq	0.0467

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A15.ii. Regressions *subsample 79*, *subsample 90* and *subsample 00* using *KldB2010* - full output tables

Table A63: *Regressions (18), (19), (20) and (21), the impact technological age on the likelihood to change occupations, overall sample, subsample 79, subsample 90 and subsample 00, KldB2010, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coeffi-cients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coeffi-cients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coeffi-cients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coeffi-cients of log tech age (*KldB2010*) *subsample 00* (21)
agriculture (11)	-0.0263**	1.0182***	0.3436***	0.03
	(0.0093)	(0.2603)	(0.0840)	(0.0167)
gardening (12)	0.0199	1.2719***	0.149	0.033
	(0.0113)	(0.3014)	(0.0823)	(0.0209)
raw_material_prod (21)	0.0379***	0.5456***	0.3336***	0.0783***
	(0.0102)	(0.1528)	(0.0865)	(0.0203)
plastic_wood_process (22)	0.0062	0.8348***	0.0528	0.0722***
	(0.0043)	(0.0659)	(0.0410)	(0.0086)
paper_process (23)	-0.0129**	0.0561*	-0.0022	0.0322*
	(0.0046)	(0.0277)	(0.0217)	(0.0153)
metal_making (24)	0.0041	0.7062***	0.1642***	0.0380***
	(0.0027)	(0.0461)	(0.0307)	(0.0056)
machine_car_build (25)	0.0182***	0.3038***	0.0503***	0.0496***
	(0.0022)	(0.0240)	(0.0144)	(0.0053)
electrical_engineer (26)	0.0185***	0.0456**	0.0861***	0.0747***
	(0.0038)	(0.0150)	(0.0170)	(0.0119)
tech_research_construction (27)	0.0144***	0.0881***	0.0175	0.1455***
	(0.0027)	(0.0090)	(0.0093)	(0.0232)
textile_process (28)	0.1041***	2.1000***	0.2815***	0.1320***
	(0.0108)	(0.2252)	(0.0713)	(0.0216)
food_process (29)	0.0370***	1.9489***	0.3225***	0.0912***
	(0.0078)	(0.1490)	(0.0531)	(0.0163)
architecture (31)	0.0430***	0.0979***	0.0707***	0.1337**
	(0.0046)	(0.0155)	(0.0133)	(0.0480)
construction (32)	0.2417***	1.6670***	0.3268***	0.2621***
	(0.0109)	(0.1546)	(0.0652)	(0.0213)
interior_constr (33)	0.1277***	1.4543***	0.2951***	0.1756***
	(0.0099)	(0.1641)	(0.0665)	(0.0218)
build_engineer (34)	0.0639***	0.8944***	0.2448***	0.0972***
	(0.0054)	(0.0955)	(0.0395)	(0.0118)
math_bio_chem (41)	-0.0279***	0.0133	-0.0368**	0.0244
	(0.0036)	(0.0145)	(0.0125)	(0.0182)
geo (42)	0.0477**	0.1098	0.0295	-0.1658
	(0.0184)	(0.0662)	(0.0400)	(0.2735)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 00* (21)
IT (43)	-0.0680***	-0.0434*	-0.1204***	0.0976***
	(0.0074)	(0.0202)	(0.0185)	(0.0278)
logistics (51)	-0.0719***	0.1652***	-0.0726***	0.0190
	(0.0036)	(0.0272)	(0.0146)	(0.0109)
drivers (52)	0.0287***	1.0185***	0.1879***	0.0987***
	(0.0061)	(0.1195)	(0.0483)	(0.0128)
safety (53)	-0.0476***	0.0868**	-0.1055***	-0.0559*
	(0.0053)	(0.0272)	(0.0146)	(0.0252)
cleaning_service (54)	0.1103***	2.0247***	0.5516***	0.1359*
	(0.0320)	(0.1912)	(0.0845)	(0.0562)
purchasing_sales (61)	0.0046	0.1708***	0.0249*	0.0551*
	(0.0032)	(0.0138)	(0.0102)	(0.0215)
retail (62)	-0.0223***	0.7035***	0.0373*	0.0431***
	(0.0041)	(0.0468)	(0.0167)	(0.0119)
tourism (63)	0.0272**	0.7964***	0.2043***	0.0866**
	(0.0089)	(0.0856)	(0.0288)	(0.0270)
management (71)	0.0208***	0.0555***	-0.0258***	0.1563***
	(0.0016)	(0.0056)	(0.0059)	(0.0194)
finance (72)	-0.0026	0.0007	-0.0698***	0.0757**
	(0.0026)	(0.0056)	(0.0116)	(0.0293)
law (73)	-0.0306***	0.0458	-0.0747***	0.2480***
	(0.0071)	(0.0323)	(0.0169)	(0.0480)
medical (81)	0.0401***	0.1869***	0.0036	0.0445***
	(0.0021)	(0.0208)	(0.0060)	(0.0104)
wellness (82)	0.0940***	2.1010***	0.1134***	0.1070***
	(0.0080)	(0.2663)	(0.0326)	(0.0225)
education (83)	0.0017	1.2413***	-0.0131	0.0034
	(0.0033)	(0.0873)	(0.0121)	(0.0085)
teaching (84)	-0.0265***	0.1578***	-0.0403***	0.0501*
	(0.0046)	(0.0351)	(0.0112)	(0.0219)
social_science (91)	-0.0299**	-0.0278	-0.0543	0.2070***
	(0.0109)	(0.0541)	(0.0304)	(0.0600)
marketing (92)	-0.0069	0.0632**	0.0674*	0.1308**
	(0.0078)	(0.0195)	(0.0302)	(0.0451)
craftwork (93)	0.0391**	1.2874***	0.0986**	0.0969**
	(0.0123)	(0.1442)	(0.0377)	(0.0346)
entertainment (94)	0.0965***	0.5767***	0.2094***	0.1308***
	(0.0147)	(0.1439)	(0.0604)	(0.0357)
age_squared	0	-0.0001***	-0.0001***	-0.0000***
	0.0000	0.0000	0.0000	0.0000
lvl_of_performance	-0.0215***	-0.0271***	-0.0211***	-0.0151***
	(0.0006)	(0.0013)	(0.0012)	(0.0019)
formerjobs	-0.0202***	-0.0229***	-0.0334***	-0.0382***
	(0.0002)	(0.0004)	(0.0004)	(0.0006)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 00* (21)
days_unemployed	0.0000***	0	-0.0000***	-0.0000***
	0.0000	0.0000	0.0000	0.0000
experience	0.0061***	0.0272***	0.0172***	0.0186***
	0.0000	(0.0002)	(0.0001)	(0.0002)
1.vocTrain	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
2.vocTrain	-0.0920***	-0.0733***	-0.1157***	-0.0971***
	(0.0012)	(0.0021)	(0.0028)	(0.0048)
3.vocTrain	-0.0572***	-0.0471***	-0.0998***	-0.0720***
	(0.0029)	(0.0062)	(0.0063)	(0.0090)
4.vocTrain	-0.1395***	-0.1336***	-0.1789***	-0.1689***
	(0.0021)	(0.0048)	(0.0045)	(0.0067)
5.vocTrain	-0.2142***	-0.1879***	-0.2618***	-0.2478***
	(0.0021)	(0.0047)	(0.0046)	(0.0071)
1.industry	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
2.industry	-0.0275***	-0.0097	-0.0482***	-0.0547***
	(0.0027)	(0.0061)	(0.0054)	(0.0081)
3.industry	-0.0311***	-0.0186**	-0.0487***	-0.0585***
	(0.0026)	(0.0057)	(0.0050)	(0.0077)
4.industry	-0.0394***	-0.0378***	-0.0533***	-0.0605***
	(0.0026)	(0.0058)	(0.0051)	(0.0077)
5.industry	-0.0091***	0.0114*	-0.0348***	-0.0321***
	(0.0026)	(0.0057)	(0.0050)	(0.0077)
6.industry	0.0416***	0.0567***	0.0194**	0.0375***
	(0.0032)	(0.0069)	(0.0062)	(0.0094)
7.industry	-0.0022	0.0117*	-0.0380***	0.0092
	(0.0026)	(0.0057)	(0.0049)	(0.0076)
8.industry	0.0007	0.0253***	-0.0288***	-0.0180*
	(0.0025)	(0.0055)	(0.0048)	(0.0073)
9.industry	-0.0189***	-0.0119*	-0.0371***	-0.0329***
	(0.0027)	(0.0060)	(0.0052)	(0.0076)
10.industry	0.0061*	0.0122*	-0.0180***	0.0149*
	(0.0025)	(0.0056)	(0.0048)	(0.0072)
11.industry	-0.0157***	-0.0168**	-0.0349***	-0.0039
	(0.0027)	(0.0061)	(0.0052)	(0.0078)
12.industry	-0.0345***	-0.0434***	-0.0530***	(0.0007)
	(0.0027)	(0.0061)	(0.0052)	(0.0079)
13.industry	-0.0466***	-0.0522***	-0.0553***	-0.0585***
	(0.0027)	(0.0059)	(0.0051)	(0.0081)
1.state	0	0	0	0
	(.)	(.)	(.)	(.)
2.state	-0.0139***	-0.0106*	-0.0102*	-0.0157*
	(0.0025)	(0.0051)	(0.0050)	(0.0069)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 00* (21)
3.state	0.0028	0.0079	-0.0038	-0.0051
	(0.0027)	(0.0059)	(0.0055)	(0.0076)
4.state	-0.0058	-0.0046	-0.0061	-0.0163
	(0.0038)	(0.0079)	(0.0078)	(0.0110)
5.state	-0.0069*	-0.0069	-0.006	-0.0125
	(0.0027)	(0.0058)	(0.0054)	(0.0074)
6.state	-0.0128***	-0.0051	-0.0143*	-0.0203**
	(0.0028)	(0.0062)	(0.0057)	(0.0077)
7.state	0.0023	0.0015	0.0099	-0.0069
	(0.0032)	(0.0068)	(0.0064)	(0.0088)
8.state	-0.0068*	-0.0029	-0.007	-0.0243**
	(0.0028)	(0.0061)	(0.0057)	(0.0078)
9.state	-0.0063*	-0.0022	-0.0016	-0.0245**
	(0.0028)	(0.0062)	(0.0057)	(0.0077)
10.state	-0.0055	-0.0134	0.0114	0.0006
	(0.0049)	(0.0103)	(0.0100)	(0.0132)
11.state	-0.0018	0.0018	0.0013	0.002
	(0.0032)	(0.0080)	(0.0062)	(0.0083)
12.state	0.0111**		0.0066	0.0159
	(0.0038)		(0.0068)	(0.0090)
13.state	0.0123**		0.0083	0.011
	(0.0048)		(0.0079)	(0.0102)
14.state	0.0085*		0.0058	0.0099
	(0.0037)		(0.0066)	(0.0089)
15.state	0.0164***		0.0127	0.0146
	(0.0041)		(0.0071)	(0.0093)
16.state	0.0113**		0.0071	0.0025
	(0.0043)		(0.0074)	(0.0098)
11.KldB2010	0	0	0	0
	(.)	(.)	(.)	(.)
12.KldB2010	-0.0151**	0.0040	-0.0363**	0.0530**
	(0.0059)	(0.0131)	(0.0123)	(0.0185)
21.KldB2010	-0.0434***	-0.0620***	(0.0191)	0.0001
	(0.0060)	(0.0123)	(0.0134)	(0.0209)
22.KldB2010	-0.0522***	-0.0657***	-0.0382**	-0.0298
	(0.0052)	(0.0114)	(0.0117)	(0.0172)
23.KldB2010	-0.0827***	-0.1211***	-0.0678***	-0.0625**
	(0.0057)	(0.0123)	(0.0134)	(0.0202)
24.KldB2010	-0.0581***	-0.0841***	-0.0453***	-0.0362*
	(0.0050)	(0.0110)	(0.0110)	(0.0162)
25.KldB2010	-0.0743***	-0.1176***	-0.0556***	-0.0671***
	(0.0050)	(0.0111)	(0.0109)	(0.0161)
26.KldB2010	-0.0964***	-0.1542***	-0.0995***	-0.0712***
	(0.0053)	(0.0119)	(0.0123)	(0.0181)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 00* (21)
27.KldB2010	-0.0915***	-0.1520***	-0.0775***	-0.1674***
	(0.0053)	(0.0115)	(0.0119)	(0.0233)
28.KldB2010	-0.0430***	-0.0416***	0.0043	(0.0049)
	(0.0056)	(0.0119)	(0.0125)	(0.0215)
29.KldB2010	-0.0487***	-0.0365**	-0.0336**	-0.0507**
	(0.0053)	(0.0115)	(0.0114)	(0.0172)
31.KldB2010	-0.1222***	-0.1671***	-0.1468***	-0.1423***
	(0.0066)	(0.0145)	(0.0151)	(0.0417)
32.KldB2010	-0.0699***	-0.0713***	-0.0740***	-0.0197
	(0.0051)	(0.0112)	(0.0110)	(0.0166)
33.KldB2010	-0.0484***	-0.0423***	-0.0544***	(0.0299)
	(0.0056)	(0.0120)	(0.0120)	(0.0180)
34.KldB2010	-0.0667***	-0.0778***	-0.0793***	(0.0225)
	(0.0054)	(0.0119)	(0.0119)	(0.0177)
41.KldB2010	-0.0676***	-0.1337***	-0.0248*	-0.0567**
	(0.0055)	(0.0120)	(0.0126)	(0.0216)
42.KldB2010	-0.2362***	-0.3336***	-0.2679***	-0.0868
	(0.0295)	(0.0666)	(0.0756)	(0.1886)
43.KldB2010	-0.0759***	-0.1963***	(0.0166)	-0.1517***
	(0.0075)	(0.0185)	(0.0176)	(0.0265)
51.KldB2010	-0.0344***	-0.0866***	(0.0208)	(0.0325)
	(0.0051)	(0.0111)	(0.0110)	(0.0166)
52.KldB2010	-0.1105***	-0.1298***	-0.1075***	-0.0961***
	(0.0051)	(0.0111)	(0.0109)	(0.0164)
53.KldB2010	-0.0668***	-0.1169***	-0.0278*	-0.0447
	(0.0061)	(0.0131)	(0.0134)	(0.0253)
54.KldB2010	-0.0452***	-0.0229	-0.0129	0.0103
	(0.0054)	(0.0119)	(0.0119)	(0.0177)
61.KldB2010	-0.0835***	-0.1465***	-0.0858***	-0.0882***
	(0.0054)	(0.0116)	(0.0121)	(0.0221)
62.KldB2010	-0.0555***	-0.0745***	-0.0583***	-0.0464**
	(0.0051)	(0.0113)	(0.0111)	(0.0168)
63.KldB2010	-0.0839***	-0.1329***	-0.1001***	-0.0567**
	(0.0057)	(0.0125)	(0.0125)	(0.0197)
71.KldB2010	-0.1391***	-0.1901***	-0.1056***	-0.2240***
	(0.0050)	(0.0112)	(0.0111)	(0.0214)
72.KldB2010	-0.1337***	-0.1927***	-0.0877***	-0.1824***
	(0.0054)	(0.0121)	(0.0137)	(0.0269)
73.KldB2010	-0.0686***	-0.1463***	-0.0243	-0.2248***
	(0.0075)	(0.0164)	(0.0164)	(0.0406)
81.KldB2010	-0.1861***	-0.2043***	-0.1813***	-0.1789***
	(0.0055)	(0.0123)	(0.0119)	(0.0188)
82.KldB2010	-0.0739***	-0.0243	-0.0795***	-0.0839**
	(0.0070)	(0.0154)	(0.0162)	(0.0257)

Dependent variable: occupation change in $t+1$	Occupation specific coeffi-cients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coeffi-cients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coeffi-cients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coeffi-cients of log tech age (*KldB2010*) *subsample 00* (21)
83.KldB2010	-0.0955***	-0.0762***	-0.1094***	-0.0693***
	(0.0055)	(0.0121)	(0.0118)	(0.0181)
84.KldB2010	-0.0871***	-0.1064***	-0.0952***	-0.0984***
	(0.0065)	(0.0143)	(0.0137)	(0.0247)
91.KldB2010	-0.0421***	-0.0964***	(0.0246)	-0.1527***
	(0.0090)	(0.0200)	(0.0231)	(0.0464)
92.KldB2010	-0.0993***	-0.1427***	-0.1478***	-0.1363***
	(0.0081)	(0.0165)	(0.0246)	(0.0371)
93.KldB2010	-0.0422***	-0.0601***	-0.0303	0.0097
	(0.0076)	(0.0157)	(0.0166)	(0.0282)
94.KldB2010	-0.1086***	-0.1454***	-0.1147***	-0.0690*
	(0.0096)	(0.0215)	(0.0209)	(0.0298)
1979.year	0.0000	0.0000		
	(.)	(.)		
1980.year	-0.0064***	-0.0147***		
	(0.0006)	(0.0007)		
1981.year	-0.0208***	-0.0375***		
	(0.0007)	(0.0009)		
1982.year	-0.0318***	-0.0572***		
	(0.0007)	(0.0012)		
1983.year	-0.0395***	-0.0743***		
	(0.0008)	(0.0015)		
1984.year	-0.0447***	-0.0892***		
	(0.0009)	(0.0018)		
1985.year	-0.0499***	-0.1040***		
	(0.0009)	(0.0021)		
1986.year	-0.0534***	-0.1177***		
	(0.0010)	(0.0024)		
1987.year	-0.0612***	-0.1370***		
	(0.0011)	(0.0027)		
1988.year	-0.0645***	-0.1523***		
	(0.0012)	(0.0031)		
1989.year	-0.0676***	-0.1667***		
	(0.0013)	(0.0034)		
1990.year	-0.0724***		0	
	(0.0014)		(.)	
1991.year	-0.0779***		(0.0011)	
	(0.0015)		(0.0006)	
1992.year	-0.0789***		-0.0026**	
	(0.0016)		(0.0009)	
1993.year	-0.0904***		-0.0108***	
	(0.0017)		(0.0012)	
1994.year	-0.0984***		-0.0173***	
	(0.0018)		(0.0015)	

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 79* (19)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 90* (20)	Occupation specific coefficients of log tech age (*KldB2010*) *subsample 00* (21)
1995.year	-0.1042***		-0.0225***	
	(0.0019)		(0.0018)	
1996.year	-0.1127***		-0.0298***	
	(0.0020)		(0.0021)	
1997.year	-0.1126***		-0.0302***	
	(0.0021)		(0.0024)	
1998.year	-0.1157***		-0.0328***	
	(0.0023)		(0.0027)	
1999.year	-0.1192***		-0.0343***	
	(0.0024)		(0.0031)	
2000.year	-0.1237***			0
	(0.0025)			(.)
2001.year	-0.1315***			-0.0083***
	(0.0026)			(0.0007)
2002.year	-0.1424***			-0.0218***
	(0.0027)			(0.0012)
2003.year	-0.1507***			-0.0349***
	(0.0028)			(0.0017)
2004.year	-0.1562***			-0.0462***
	(0.0030)			(0.0022)
2005.year	-0.1641***			-0.0604***
	(0.0031)			(0.0027)
2006.year	-0.1675***			-0.0704***
	(0.0032)			(0.0032)
employment_change	-0.0101***	-0.0021*	-0.0144***	0.0044**
	(0.0005)	(0.0010)	(0.0008)	(0.0016)
_cons	0.4292***	0.5181***	0.5017***	0.3690***
	(0.0057)	(0.0130)	(0.0127)	(0.0195)
N	10,870,916	3,843,022	4,314,945	2,712,949
R-sq	0.0467	0.0514	0.049	0.0598

Note: Dependent variable is occupation change in period $t+1$*. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A15.iii. Regression *overall sample* allowing for unemployment - full output table

Table A64: *Regressions (5) and (22), the impact technological age on the likelihood to change occupations, overall sample and overall sample with unemployment, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample* with unemployment (22)
agriculture_fishing (1)	0.0068	0.0158*
	(.0061)	(.0073)
miners_stone_workers (2)	0.0879***	0.1292***
	(.0126)	(.0164)
ceramic_glas (3)	-0.0694***	-0.0233
	(.0153)	(.0172)
chemistry_synthetic_workers (4)	-0.0739***	-0.0697***
	(.0041)	(.0046)
paper_print (5)	-0.0369***	-0.0118
	(.0054)	(.0061)
woodworking (6)	0.1704	-0.0895
	(.1014)	(.0714)
metal_works (7)	-0.0138***	-0.0190***
	(.0035)	(.0041)
mechanics (8)	0.0472***	0.0622***
	(.0023)	(.0027)
electricians (9)	0.0598***	0.0729***
	(.0032)	(.0036)
assembly (10)	-0.0591***	-0.0620***
	(.0051)	(.0060)
textile_clothing_leather_fur (11)	0.1171***	0.1516***
	(.0116)	(.0135)
food (12)	0.0950***	0.0975***
	(.0074)	(.0081)
construction (13)	0.2608***	0.3243***
	(.0088)	(.0112)
interior_construction (14)	0.0506***	0.1539***
	(.0101)	(.0123)
carpenter (15)	0.0980***	0.1628***
	(.0073)	(.0090)
painter (16)	0.1099***	0.2025***
	(.0080)	(.0109)
product_testing (17)	-0.0989***	-0.0882***
	(.0057)	(.0060)
machinist (18)	0.0104	0.0039
	(.0060)	(.0071)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample* with unemployment (22)
engineer_math_chem (19)	0.0247***	-0.0032
	(.0029)	(.0032)
technical_specilaist (20)	0.0418***	0.0277***
	(.0023)	(.0025)
goods_merchants (21)	0.0155***	0.0060*
	(.0029)	(.0027)
service_merchants (22)	-0.0063*	-0.0053*
	(.0027)	(.0026)
traffic (23)	-0.0163***	-0.0508***
	(.0033)	(.0036)
administration (24)	0.0194***	-0.0079***
	(.0016)	(.0017)
regulatory_safety (25)	-0.0561***	-0.0407***
	(.0049)	(.0051)
writing_art (26)	0.0255***	0.0018
	(.0056)	(.0057)
healthcare (27)	0.0520***	0.0042*
	(.0020)	(.0020)
social_education_science (28)	0.0251***	-0.0634***
	(.0028)	(.0028)
age_sqared	0.0000***	0.0001***
	.0000	.0000
lvl_of_performance	-0.0152***	-0.0173***
	(.0005)	(.0005)
ln_formerjobs	-0.0184***	-0.0162***
	(.0002)	(.0002)
days_unemployed	-0.0000***	0.0000***
	.0000	.0000
experience	0.0057***	0.0049***
	.0000	.0000
employment_change	-0.0099***	-0.0138***
	(.0005)	(.0005)
1.vocTrain	0	0
	(.)	(.)
2.vocTrain	-0.0975***	0.0216***
	(.0011)	(.0006)
3.vocTrain	-0.0728***	-0.0186***
	(.0026)	(.0017)
4.vocTrain	-0.1450***	-0.0140***
	(.0019)	(.0014)
5.vocTrain	-0.2126***	-0.0916***
	(.0020)	(.0016)
1.industry	0	0
	(.)	(.)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample* with unemployment (22)
2.industry	-0.0280***	-0.0344***
	(.0025)	(.0026)
3.industry	-0.0316***	-0.0367***
	(.0023)	(.0024)
4.industry	-0.0443***	-0.0485***
	(.0023)	(.0024)
5.industry	-0.0114***	-0.0110***
	(.0023)	(.0024)
6.industry	0.0106***	0.0352***
	(.0031)	(.0031)
7.industry	-0.0121***	-0.0026
	(.0023)	(.0024)
8.industry	-0.0021	0.0023
	(.0022)	(.0023)
9.industry	-0.0283***	-0.0168***
	(.0024)	(.0025)
10.industry	-0.0015	0.0025
	(.0022)	(.0023)
11.industry	-0.0243***	-0.0165***
	(.0024)	(.0025)
12.industry	-0.0363***	-0.0348***
	(.0024)	(.0024)
13.industry	-0.0433***	-0.0523***
	(.0024)	(.0025)
1.state	0	0
	(.)	(.)
2.state	-0.0114***	-0.0180***
	(.0022)	(.0022)
3.state	0.0022	0.0002
	(.0025)	(.0025)
4.state	-0.0051	-0.0048
	(.0034)	(.0036)
5.state	-0.0037	-0.0088***
	(.0024)	(.0025)
6.state	-0.0066**	-0.0133***
	(.0025)	(.0026)
7.state	0.0063*	-0.0014
	(.0029)	(.0029)
8.state	-0.0033	-0.0091***
	(.0025)	(.0026)
9.state	-0.0023	-0.0085**
	(.0025)	(.0026)
10.state	-0.0005	-0.0081
	(.0045)	(.0047)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample* with unemployment (22)
11.state	-0.0028	-0.0059
	(.0029)	(.0030)
12.state	0.0134***	0.0151***
	(.0034)	(.0037)
13.state	0.0135**	0.0176***
	(.0042)	(.0045)
14.state	0.0141***	0.0097**
	(.0033)	(.0036)
15.state	0.0179***	0.0143***
	(.0037)	(.0040)
16.state	0.0182***	0.0135**
	(.0038)	(.0042)
1.KldB88	0	0
	(.)	(.)
2.KldB88	0.0034	-0.0427***
	(.0048)	(.0050)
3.KldB88	0.0185**	-0.0334***
	(.0061)	(.0062)
4.KldB88	0.0097**	-0.0369***
	(.0035)	(.0036)
5.KldB88	-0.0255***	-0.0722***
	(.0042)	(.0042)
6.KldB88	0.0280***	-0.0146*
	(.0056)	(.0061)
7.KldB88	-0.0037	-0.0493***
	(.0032)	(.0033)
8.KldB88	-0.0309***	-0.0813***
	(.0030)	(.0030)
9.KldB88	-0.0472***	-0.0998***
	(.0033)	(.0033)
10.KldB88	0.0217***	-0.0124***
	(.0033)	(.0034)
11.KldB88	0.0027	-0.0405***
	(.0039)	(.0038)
12.KldB88	-0.0051	-0.0494***
	(.0034)	(.0034)
13.KldB88	-0.0356***	-0.0495***
	(.0031)	(.0032)
14.KldB88	0.0119**	-0.0378***
	(.0041)	(.0042)
15.KldB88	-0.0267***	-0.0683***
	(.0041)	(.0040)
16.KldB88	-0.0365***	-0.0726***
	(.0042)	(.0042)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample* with unemployment (22)
17.KldB88	0.0336***	0.0061
	(.0035)	(.0035)
18.KldB88	-0.0113**	-0.0562***
	(.0039)	(.0041)
19.KldB88	-0.1131***	-0.1256***
	(.0038)	(.0040)
20.KldB88	-0.0838***	-0.1186***
	(.0033)	(.0033)
21.KldB88	-0.0526***	-0.0950***
	(.0031)	(.0030)
22.KldB88	-0.0875***	-0.1419***
	(.0036)	(.0035)
23.KldB88	-0.0439***	-0.0590***
	(.0029)	(.0030)
24.KldB88	-0.1117***	-0.1293***
	(.0030)	(.0030)
25.KldB88	-0.0253***	-0.0483***
	(.0041)	(.0042)
26.KldB88	-0.0891***	-0.1012***
	(.0050)	(.0047)
27.KldB88	-0.1598***	-0.1810***
	(.0036)	(.0034)
28.KldB88	-0.1014***	-0.0741***
	(.0037)	(.0035)
1979.year	0	0
	(.)	(.)
1980.year	-0.0069***	0.0025***
	(.0006)	(.0006)
1981.year	-0.0191***	-0.0034***
	(.0007)	(.0007)
1982.year	-0.0326***	-0.0123***
	(.0007)	(.0007)
1983.year	-0.0427***	-0.0224***
	(.0008)	(.0008)
1984.year	-0.0495***	-0.0306***
	(.0008)	(.0009)
1985.year	-0.0548***	-0.0402***
	(.0009)	(.0009)
1986.year	-0.0600***	-0.0451***
	(.0010)	(.0010)
1987.year	-0.0681***	-0.0552***
	(.0011)	(.0011)
1988.year	-0.0754***	-0.0650***
	(.0012)	(.0012)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample* with unemployment (22)
1989.year	-0.0782***	-0.0719***
	(.0013)	(.0013)
1990.year	-0.0840***	-0.0791***
	(.0014)	(.0014)
1991.year	-0.0914***	-0.0833***
	(.0015)	(.0014)
1992.year	-0.0917***	-0.0841***
	(.0016)	(.0015)
1993.year	-0.1048***	-0.0935***
	(.0017)	(.0016)
1994.year	-0.1160***	-0.1011***
	(.0018)	(.0017)
1995.year	-0.1252***	-0.1000***
	(.0019)	(.0018)
1996.year	-0.1311***	-0.1144***
	(.0020)	(.0019)
1997.year	-0.1358***	-0.1136***
	(.0021)	(.0020)
1998.year	-0.1434***	-0.1181***
	(.0022)	(.0021)
1999.year	-0.1486***	-0.1233***
	(.0023)	(.0023)
2000.year	-0.1531***	-0.1283***
	(.0024)	(.0024)
2001.year	-0.1625***	-0.1306***
	(.0025)	(.0025)
2002.year	-0.1749***	-0.1403***
	(.0026)	(.0026)
2003.year	-0.1851***	-0.1495***
	(.0028)	(.0027)
2004.year	-0.1946***	-0.1584***
	(.0029)	(.0028)
2005.year	-0.2059***	-0.1797***
	(.0030)	(.0029)
2006.year	-0.2144***	-0.1975***
	(.0031)	(.0031)
Constant	0.3665***	0.2824***
	(.0039)	(.0039)
N	11,030,551	12,355,511
R-sq	0.0515	0.0227

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A15.iv. Regression extended sample using *KldB2010* - full output table

Because the occupation change regression uses occupation change in $t+1$ as a dependent variable and the *SIAB Data* ends in 2012, there is no available knowledge whether workers leave their occupations in 2013. Therefore, the year 2012 is not part of the regression as all observations in 2012 would show no occupation change in $t+1$.

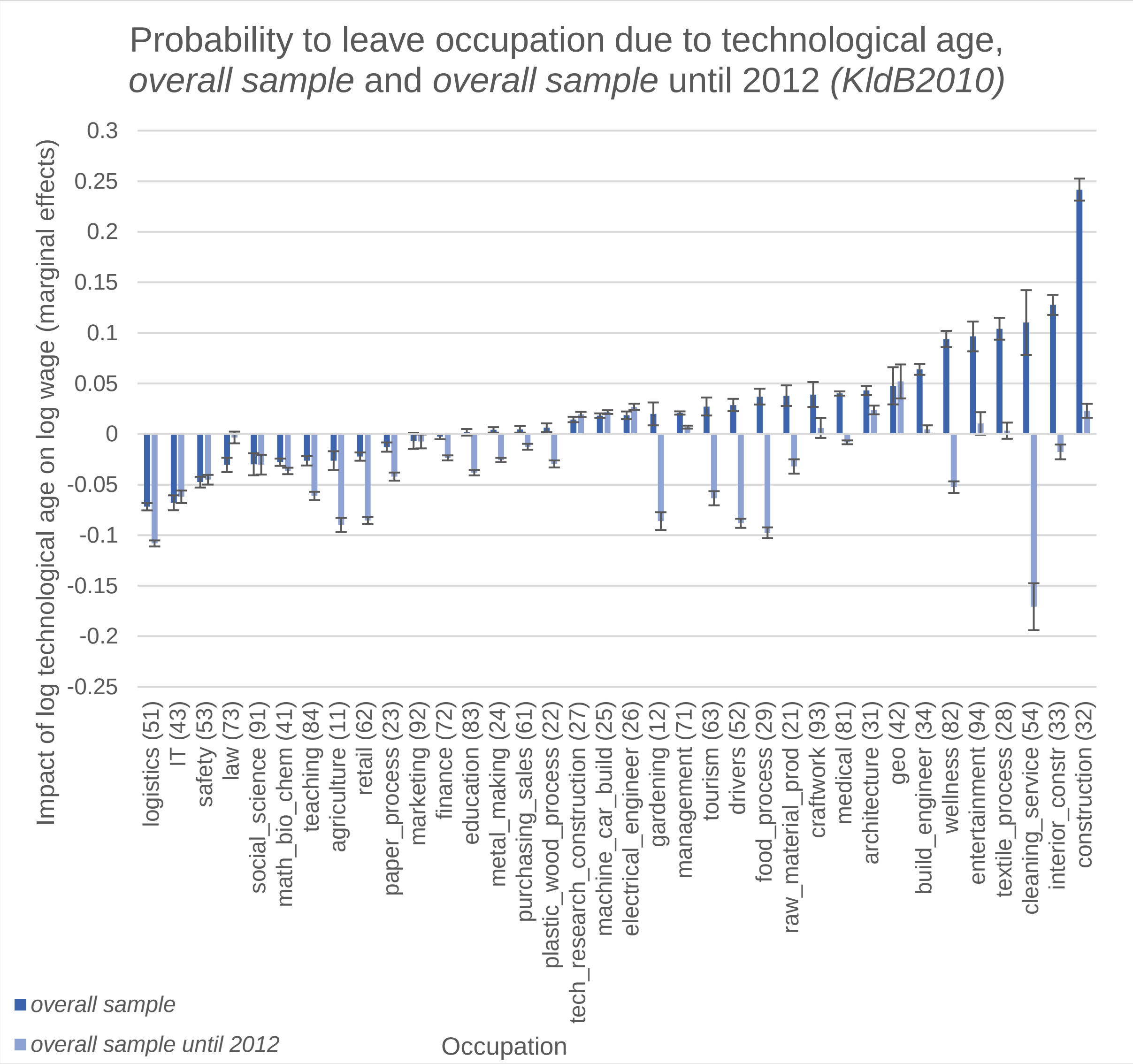

Figure A10: *Probability to leave occupation due to technological age, overall sample and overall sample until 2012 (KldB2010)*

Note: Marginal effects of regression (18) and regression (23), ordered by size of marginal effects in regression (18) Including standard errors. Regression (18) and (23) can be found in Table A66.

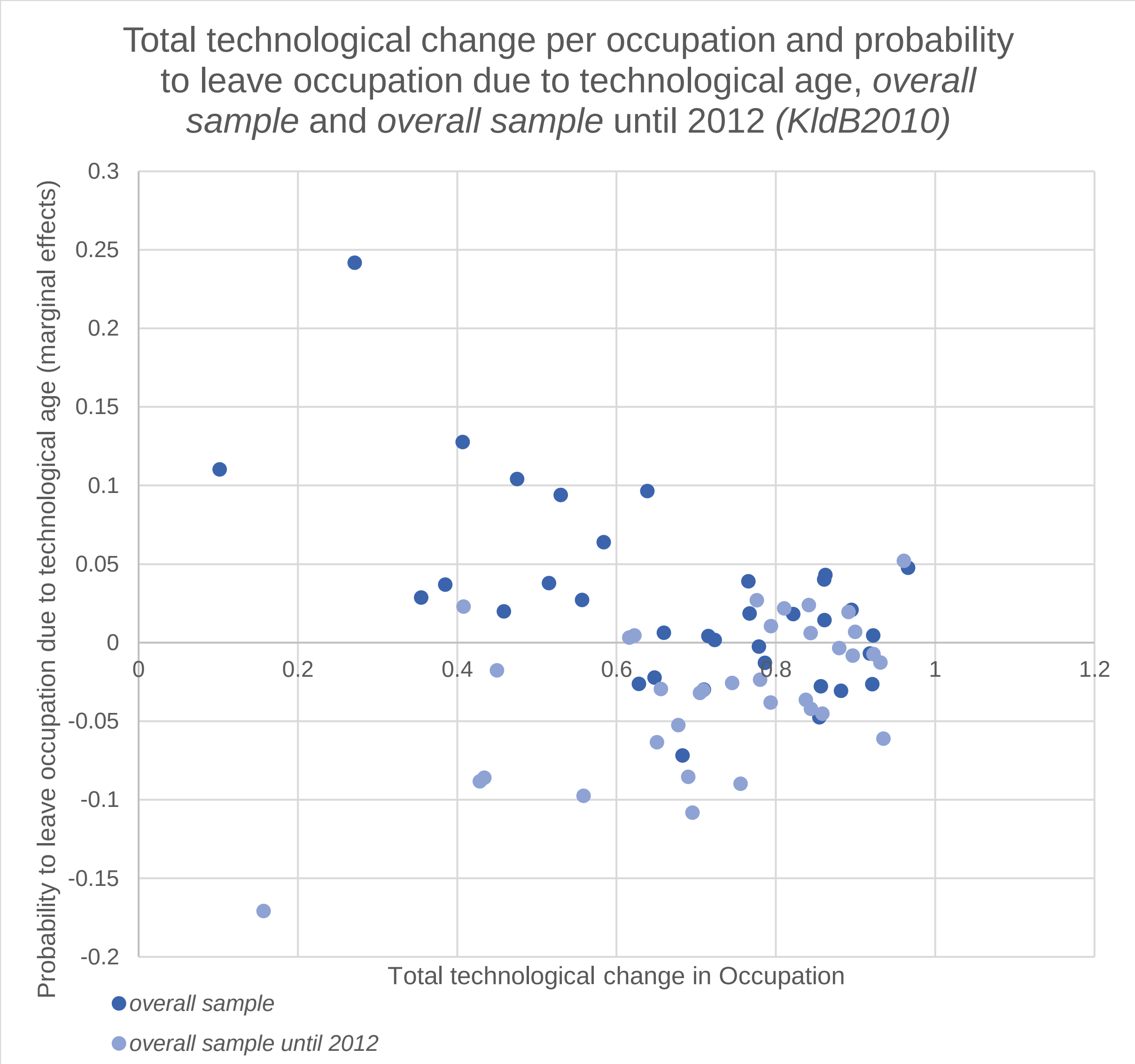

Figure A11: *Total technological change per occupation and probability to leave occupation due to technological age, overall sample and overall sample until 2012 (KldB2010)*

Note: Marginal effects of regression (18), regression (23) and overall technological change per occupation according to Table A11 to Table A15 in each timeframe. Regression (18) and (23) can be found in Table A66.

Table A65: *Linear correlation between the marginal effects of regressions (18), (22) and (8) and technological change per occupation*

Correlation between	**Sample Period**	**Correlation**
marginal effects likelihood to leave occupation *(KldB2010)*	*overall sample*	-0.6114
technological change	*overall sample*	
marginal effects likelihood to leave occupation *(KldB2010), extended sample period*	*extended overall sample*	0.5566
technological change	*extended overall sample*	
marginal effects likelihood to leave occupation	*subsample 00*	0.3904
technological change	*subsample 00*	

Note: The correlation does not include the observation for IT (43).

Table A66: *Regressions (18) and (23), the impact technological age on the likelihood to change occupations, overall sample and overall sample until 2012, KldB2010, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
agriculture (11)	-0.0263**	-0.0899***
	(0.0093)	(0.0069)
gardening (12)	0.0199	-0.0861***
	(0.0113)	(0.0088)
raw_material_prod (21)	0.0379***	-0.0321***
	(0.0102)	(0.0071)
plastic_wood_process (22)	0.0062	-0.0296***
	(0.0043)	(0.0035)
paper_process (23)	-0.0129**	-0.0421***
	(0.0046)	(0.0040)
metal_making (24)	0.0041	-0.0257***
	(0.0027)	(0.0021)
machine_car_build (25)	0.0182***	0.0217***
	(0.0022)	(0.0018)
electrical_engineer (26)	0.0185***	0.0269***
	(0.0038)	(0.0031)
tech_research_construction (27)	0.0144***	0.0194***
	(0.0027)	(0.0025)
textile_process (28)	0.1041***	0.0033

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
	(0.0108)	(0.0080)
food_process (29)	0.0370***	-0.0976***
	(0.0078)	(0.0053)
architecture (31)	0.0430***	0.0238***
	(0.0046)	(0.0043)
construction (32)	0.2417***	0.0230***
	(0.0109)	(0.0069)
interior_constr (33)	0.1277***	-0.0177*
	(0.0099)	(0.0073)
build_engineer (34)	0.0639***	0.0045
	(0.0054)	(0.0041)
math_bio_chem (41)	-0.0279***	-0.0365***
	(0.0036)	(0.0032)
geo (42)	0.0477**	0.0520**
	(0.0184)	(0.0168)
IT (43)	-0.0680***	-0.0621***
	(0.0074)	(0.0062)
logistics (51)	-0.0719***	-0.1082***
	(0.0036)	(0.0030)
drivers (52)	0.0287***	-0.0883***
	(0.0061)	(0.0045)
safety (53)	-0.0476***	-0.0452***
	(0.0053)	(0.0048)
cleaning_service (54)	0.1103***	-0.1708***
	(0.0320)	(0.0232)
purchasing_sales (61)	0.0046	-0.0126***
	(0.0032)	(0.0029)
retail (62)	-0.0223***	-0.0855***
	(0.0041)	(0.0033)
tourism (63)	0.0272**	-0.0635***
	(0.0089)	(0.0070)
management (71)	0.0208***	0.0068***
	(0.0016)	(0.0015)
finance (72)	-0.0026	-0.0236***
	(0.0026)	(0.0025)
law (73)	-0.0306***	-0.0034
	(0.0071)	(0.0058)
medical (81)	0.0401***	-0.0082***
	(0.0021)	(0.0019)
wellness (82)	0.0940***	-0.0525***
	(0.0080)	(0.0057)
education (83)	0.0017	-0.0382***
	(0.0033)	(0.0027)
teaching (84)	-0.0265***	-0.0612***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
	(0.0046)	(0.0041)
social_science (91)	-0.0299**	-0.0303**
	(0.0109)	(0.0098)
marketing (92)	-0.0069	-0.0073
	(0.0078)	(0.0069)
craftwork (93)	0.0391**	0.006
	(0.0123)	(0.0098)
entertainment (94)	0.0965***	0.0104
	(0.0147)	(0.0112)
age_squared	0	0.0000***
	0.0000	0.0000
lvl_of_performance	-0.0215***	-0.0160***
	(0.0006)	(0.0005)
formerjobs	-0.0202***	-0.0200***
	(0.0002)	(0.0002)
days_unemployed	0.0000***	0.0000***
	0.0000	0.0000
experience	0.0061***	0.0050***
	0.0000	0.0000
1.vocTrain	0	0
	(.)	(.)
2.vocTrain	-0.0920***	-0.0964***
	(0.0012)	(0.0011)
3.vocTrain	-0.0572***	-0.0623***
	(0.0029)	(0.0025)
4.vocTrain	-0.1395***	-0.1427***
	(0.0021)	(0.0018)
5.vocTrain	-0.2142***	-0.2122***
	(0.0021)	(0.0019)
1.industry	0	0
	(.)	(.)
2.industry	-0.0275***	-0.0243***
	(0.0027)	(0.0025)
3.industry	-0.0311***	-0.0277***
	(0.0026)	(0.0023)
4.industry	-0.0394***	-0.0343***
	(0.0026)	(0.0024)
5.industry	-0.0091***	-0.0074**
	(0.0026)	(0.0023)
6.industry	0.0416***	0.0433***
	(0.0032)	(0.0029)
7.industry	-0.0022	-0.0021
	(0.0026)	(0.0023)
8.industry	0.0007	0.0018

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
	(0.0025)	(0.0022)
9.industry	-0.0189***	-0.0183***
	(0.0027)	(0.0024)
10.industry	0.0061*	0.0115***
	(0.0025)	(0.0023)
11.industry	-0.0157***	-0.0093***
	(0.0027)	(0.0024)
12.industry	-0.0345***	-0.0269***
	(0.0027)	(0.0024)
13.industry	-0.0466***	-0.0363***
	(0.0027)	(0.0024)
1.state	0	0
	(.)	(.)
2.state	-0.0139***	-0.0123***
	(0.0025)	(0.0022)
3.state	0.0028	0.0027
	(0.0027)	(0.0024)
4.state	-0.0058	-0.0061
	(0.0038)	(0.0034)
5.state	-0.0069*	-0.0045
	(0.0027)	(0.0024)
6.state	-0.0128***	-0.0097***
	(0.0028)	(0.0025)
7.state	0.0023	0.004
	(0.0032)	(0.0028)
8.state	-0.0068*	-0.0042
	(0.0028)	(0.0025)
9.state	-0.0063*	-0.0034
	(0.0028)	(0.0025)
10.state	-0.0055	-0.0025
	(0.0049)	(0.0044)
11.state	-0.0018	-0.0005
	(0.0032)	(0.0028)
12.state	0.0111**	0.0139***
	(0.0038)	(0.0033)
13.state	0.0123**	0.0136***
	(0.0048)	(0.0040)
14.state	0.0085*	0.0095**
	(0.0037)	(0.0032)
15.state	0.0164***	0.0151***
	(0.0041)	(0.0035)
16.state	0.0113**	0.0154***
	(0.0043)	(0.0036)
11.KldB2010	0	0

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
	(.)	(.)
12.KldB2010	-0.0151**	-0.0113*
	(0.0059)	(0.0053)
21.KldB2010	-0.0434***	-0.0449***
	(0.0060)	(0.0054)
22.KldB2010	-0.0522***	-0.0557***
	(0.0052)	(0.0048)
23.KldB2010	-0.0827***	-0.0773***
	(0.0057)	(0.0052)
24.KldB2010	-0.0581***	-0.0600***
	(0.0050)	(0.0045)
25.KldB2010	-0.0743***	-0.0814***
	(0.0050)	(0.0045)
26.KldB2010	-0.0964***	-0.1034***
	(0.0053)	(0.0048)
27.KldB2010	-0.0915***	-0.0933***
	(0.0053)	(0.0048)
28.KldB2010	-0.0430***	-0.0446***
	(0.0056)	(0.0051)
29.KldB2010	-0.0487***	-0.0489***
	(0.0053)	(0.0048)
31.KldB2010	-0.1222***	-0.1192***
	(0.0066)	(0.0060)
32.KldB2010	-0.0699***	-0.0695***
	(0.0051)	(0.0047)
33.KldB2010	-0.0484***	-0.0496***
	(0.0056)	(0.0050)
34.KldB2010	-0.0667***	-0.0701***
	(0.0054)	(0.0049)
41.KldB2010	-0.0676***	-0.0627***
	(0.0055)	(0.0050)
42.KldB2010	-0.2362***	-0.2460***
	(0.0295)	(0.0207)
43.KldB2010	-0.0759***	-0.0880***
	(0.0075)	(0.0064)
51.KldB2010	-0.0344***	-0.0290***
	(0.0051)	(0.0046)
52.KldB2010	-0.1105***	-0.1095***
	(0.0051)	(0.0046)
53.KldB2010	-0.0668***	-0.0677***
	(0.0061)	(0.0056)
54.KldB2010	-0.0452***	-0.0554***
	(0.0054)	(0.0049)
61.KldB2010	-0.0835***	-0.0756***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
	(0.0054)	(0.0049)
62.KldB2010	-0.0555***	-0.0500***
	(0.0051)	(0.0046)
63.KldB2010	-0.0839***	-0.0685***
	(0.0057)	(0.0052)
71.KldB2010	-0.1391***	-0.1279***
	(0.0050)	(0.0045)
72.KldB2010	-0.1337***	-0.1221***
	(0.0054)	(0.0049)
73.KldB2010	-0.0686***	-0.0860***
	(0.0075)	(0.0064)
81.KldB2010	-0.1861***	-0.1722***
	(0.0055)	(0.0049)
82.KldB2010	-0.0739***	-0.0886***
	(0.0070)	(0.0060)
83.KldB2010	-0.0955***	-0.0919***
	(0.0055)	(0.0049)
84.KldB2010	-0.0871***	-0.0824***
	(0.0065)	(0.0058)
91.KldB2010	-0.0421***	-0.0338***
	(0.0090)	(0.0081)
92.KldB2010	-0.0993***	-0.1039***
	(0.0081)	(0.0071)
93.KldB2010	-0.0422***	-0.0394***
	(0.0076)	(0.0069)
94.KldB2010	-0.1086***	-0.0998***
	(0.0096)	(0.0086)
1979.year	0	0
	(.)	(.)
1980.year	-0.0064***	-0.0072***
	(0.0006)	(0.0006)
1981.year	-0.0208***	-0.0223***
	(0.0007)	(0.0007)
1982.year	-0.0318***	-0.0341***
	(0.0007)	(0.0007)
1983.year	-0.0395***	-0.0426***
	(0.0008)	(0.0008)
1984.year	-0.0447***	-0.0487***
	(0.0009)	(0.0008)
1985.year	-0.0499***	-0.0546***
	(0.0009)	(0.0009)
1986.year	-0.0534***	-0.0582***
	(0.0010)	(0.0010)
1987.year	-0.0612***	-0.0668***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
	(0.0011)	(0.0010)
1988.year	-0.0645***	-0.0706***
	(0.0012)	(0.0011)
1989.year	-0.0676***	-0.0738***
	(0.0013)	(0.0012)
1990.year	-0.0724***	-0.0791***
	(0.0014)	(0.0013)
1991.year	-0.0779***	-0.0849***
	(0.0015)	(0.0014)
1992.year	-0.0789***	-0.0858***
	(0.0016)	(0.0015)
1993.year	-0.0904***	-0.0981***
	(0.0017)	(0.0016)
1994.year	-0.0984***	-0.1063***
	(0.0018)	(0.0016)
1995.year	-0.1042***	-0.1124***
	(0.0019)	(0.0017)
1996.year	-0.1127***	-0.1210***
	(0.0020)	(0.0018)
1997.year	-0.1126***	-0.1210***
	(0.0021)	(0.0019)
1998.year	-0.1157***	-0.1240***
	(0.0023)	(0.0020)
1999.year	-0.1192***	-0.1276***
	(0.0024)	(0.0021)
2000.year	-0.1237***	-0.1306***
	(0.0025)	(0.0022)
2001.year	-0.1315***	-0.1366***
	(0.0026)	(0.0023)
2002.year	-0.1424***	-0.1467***
	(0.0027)	(0.0024)
2003.year	-0.1507***	-0.1541***
	(0.0028)	(0.0025)
2004.year	-0.1562***	-0.1583***
	(0.0030)	(0.0026)
2005.year	-0.1641***	-0.1652***
	(0.0031)	(0.0027)
2006.year	-0.1675***	-0.1671***
	(0.0032)	(0.0028)
2007.year		-0.1714***
		(0.0029)
2008.year		-0.1769***
		(0.0030)
2009.year		-0.1820***

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* (18)	Occupation specific coefficients of log tech age (*KldB2010*) *overall sample* until 2012 (23)
		(0.0031)
2010.year		0.0469***
		(0.0033)
2011.year		-0.1704***
		(0.0033)
employment_change	-0.0101***	-0.0166***
	(0.0005)	(0.0004)
_cons	0.4292***	0.4108***
	(0.0057)	(0.0051)
N	10,870,916	12,667,316
R-sq	0.0467	0.0607

Note: Dependent variable is occupation change in period $t+1$*. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A15.v. Regression *overall sample* imputed starting technological age - full output table

Table A67: *Regressions (5) and (24), the impact technological age on the likelihood to change occupations, overall sample and overall sample with imputed technological age, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (24)
agriculture_fishing (1)	0.0068	-0.0145*
	(.0061)	(.0061)
miners_stone_workers (2)	0.0879***	0.0795***
	(.0126)	(.0126)
ceramic_glas (3)	-0.0694***	-0.0842***
	(.0153)	(.0154)
chemistry_synthetic_workers (4)	-0.0739***	-0.0817***
	(.0041)	(.0041)
paper_print (5)	-0.0369***	-0.0461***
	(.0054)	(.0053)
woodworking (6)	0.1704	0.0926
	(.1014)	(.1046)
metal_works (7)	-0.0138***	-0.0229***
	(.0035)	(.0034)
mechanics (8)	0.0472***	0.0386***
	(.0023)	(.0023)
electricians (9)	0.0598***	0.0528***
	(.0032)	(.0032)
assembly (10)	-0.0591***	-0.0744***
	(.0051)	(.0051)
textile_clothing_leather_fur (11)	0.1171***	0.0870***
	(.0116)	(.0115)
food (12)	0.0950***	0.0620***
	(.0074)	(.0073)
construction (13)	0.2608***	0.2321***
	(.0088)	(.0088)
interior_construction (14)	0.0506***	0.0392***
	(.0101)	(.0101)
carpenter (15)	0.0980***	0.0851***
	(.0073)	(.0073)
painter (16)	0.1099***	0.0981***
	(.0080)	(.0079)
product_testing (17)	-0.0989***	-0.1164***
	(.0057)	(.0057)
machinist (18)	0.0104	0.0015
	(.0060)	(.0060)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (24)
engineer_math_chem (19)	0.0247***	0.0332***
	(.0029)	(.0029)
technical_specilaist (20)	0.0418***	0.0380***
	(.0023)	(.0023)
goods_merchants (21)	0.0155***	0.0009
	(.0029)	(.0029)
service_merchants (22)	-0.0063*	-0.0041
	(.0027)	(.0026)
traffic (23)	-0.0163***	-0.0299***
	(.0033)	(.0033)
administration (24)	0.0194***	0.0190***
	(.0016)	(.0016)
regulatory_safety (25)	-0.0561***	-0.0642***
	(.0049)	(.0049)
writing_art (26)	0.0255***	0.0184**
	(.0056)	(.0056)
healthcare (27)	0.0520***	0.0473***
	(.0020)	(.0020)
social_education_science (28)	0.0251***	0.0169***
	(.0028)	(.0028)
age_sqared	0.0000***	0.0000***
	.0000	.0000
lvl_of_performance	-0.0152***	-0.0153***
	(.0005)	(.0005)
ln_formerjobs	-0.0184***	-0.0183***
	(.0002)	(.0002)
days_unemployed	-0.0000***	-0.0000***
	.0000	.0000
experience	0.0057***	0.0057***
	.0000	.0000
employment_change	-0.0099***	-0.0092***
	(.0005)	(.0005)
1.vocTrain	0	0
	(.)	(.)
2.vocTrain	-0.0975***	-0.0972***
	(.0011)	(.0011)
3.vocTrain	-0.0728***	-0.0725***
	(.0026)	(.0026)
4.vocTrain	-0.1450***	-0.1451***
	(.0019)	(.0019)
5.vocTrain	-0.2126***	-0.2133***
	(.0020)	(.0020)
1.industry	0	0
	(.)	(.)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (24)
2.industry	-0.0280***	-0.0280***
	(.0025)	(.0025)
3.industry	-0.0316***	-0.0315***
	(.0023)	(.0023)
4.industry	-0.0443***	-0.0441***
	(.0023)	(.0023)
5.industry	-0.0114***	-0.0113***
	(.0023)	(.0023)
6.industry	0.0106***	0.0106***
	(.0031)	(.0031)
7.industry	-0.0121***	-0.0119***
	(.0023)	(.0023)
8.industry	-0.0021	-0.002
	(.0022)	(.0022)
9.industry	-0.0283***	-0.0282***
	(.0024)	(.0024)
10.industry	-0.0015	-0.0015
	(.0022)	(.0022)
11.industry	-0.0243***	-0.0243***
	(.0024)	(.0024)
12.industry	-0.0363***	-0.0361***
	(.0024)	(.0024)
13.industry	-0.0433***	-0.0432***
	(.0024)	(.0024)
1.state	0	0
	(.)	(.)
2.state	-0.0114***	-0.0114***
	(.0022)	(.0022)
3.state	0.0022	0.0022
	(.0025)	(.0025)
4.state	-0.0051	-0.005
	(.0034)	(.0034)
5.state	-0.0037	-0.0037
	(.0024)	(.0024)
6.state	-0.0066**	-0.0066**
	(.0025)	(.0025)
7.state	0.0063*	0.0064*
	(.0029)	(.0029)
8.state	-0.0033	-0.0033
	(.0025)	(.0025)
9.state	-0.0023	-0.0023
	(.0025)	(.0025)
10.state	-0.0005	-0.0004
	(.0045)	(.0045)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (24)
11.state	-0.0028	-0.0029
	(.0029)	(.0029)
12.state	0.0134***	0.0133***
	(.0034)	(.0034)
13.state	0.0135**	0.0135**
	(.0042)	(.0042)
14.state	0.0141***	0.0140***
	(.0033)	(.0033)
15.state	0.0179***	0.0179***
	(.0037)	(.0037)
16.state	0.0182***	0.0182***
	(.0038)	(.0038)
1.KldB88	0	0
	(.)	(.)
2.KldB88	0.0034	0.0012
	(.0048)	(.0048)
3.KldB88	0.0185**	0.0181**
	(.0061)	(.0061)
4.KldB88	0.0097**	0.0101**
	(.0035)	(.0036)
5.KldB88	-0.0255***	-0.0242***
	(.0042)	(.0042)
6.KldB88	0.0280***	0.0241***
	(.0056)	(.0055)
7.KldB88	-0.0037	-0.0048
	(.0032)	(.0032)
8.KldB88	-0.0309***	-0.0322***
	(.0030)	(.0030)
9.KldB88	-0.0472***	-0.0483***
	(.0033)	(.0034)
10.KldB88	0.0217***	0.0215***
	(.0033)	(.0033)
11.KldB88	0.0027	0.001
	(.0039)	(.0039)
12.KldB88	-0.0051	-0.0063
	(.0034)	(.0034)
13.KldB88	-0.0356***	-0.0383***
	(.0031)	(.0031)
14.KldB88	0.0119**	0.0100*
	(.0041)	(.0041)
15.KldB88	-0.0267***	-0.0283***
	(.0041)	(.0041)
16.KldB88	-0.0365***	-0.0386***
	(.0042)	(.0042)

Dependent variable: occupation change in $t + 1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (24)
17.KldB88	0.0336***	0.0359***
	(.0035)	(.0035)
18.KldB88	-0.0113**	-0.0124**
	(.0039)	(.0039)
19.KldB88	-0.1131***	-0.1214***
	(.0038)	(.0039)
20.KldB88	-0.0838***	-0.0850***
	(.0033)	(.0033)
21.KldB88	-0.0526***	-0.0511***
	(.0031)	(.0031)
22.KldB88	-0.0875***	-0.0897***
	(.0036)	(.0037)
23.KldB88	-0.0439***	-0.0439***
	(.0029)	(.0029)
24.KldB88	-0.1117***	-0.1140***
	(.0030)	(.0030)
25.KldB88	-0.0253***	-0.0228***
	(.0041)	(.0042)
26.KldB88	-0.0891***	-0.0887***
	(.0050)	(.0051)
27.KldB88	-0.1598***	-0.1612***
	(.0036)	(.0036)
28.KldB88	-0.1014***	-0.1011***
	(.0037)	(.0037)
1979.year	0	0
	(.)	(.)
1980.year	-0.0069***	-0.0069***
	(.0006)	(.0006)
1981.year	-0.0191***	-0.0191***
	(.0007)	(.0007)
1982.year	-0.0326***	-0.0324***
	(.0007)	(.0007)
1983.year	-0.0427***	-0.0425***
	(.0008)	(.0008)
1984.year	-0.0495***	-0.0491***
	(.0008)	(.0008)
1985.year	-0.0548***	-0.0544***
	(.0009)	(.0009)
1986.year	-0.0600***	-0.0596***
	(.0010)	(.0010)
1987.year	-0.0681***	-0.0676***
	(.0011)	(.0011)
1988.year	-0.0754***	-0.0748***
	(.0012)	(.0012)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age, imputed technology start numbers *overall sample* (24)
1989.year	-0.0782***	-0.0775***
	(.0013)	(.0013)
1990.year	-0.0840***	-0.0832***
	(.0014)	(.0014)
1991.year	-0.0914***	-0.0905***
	(.0015)	(.0015)
1992.year	-0.0917***	-0.0908***
	(.0016)	(.0016)
1993.year	-0.1048***	-0.1036***
	(.0017)	(.0017)
1994.year	-0.1160***	-0.1147***
	(.0018)	(.0018)
1995.year	-0.1252***	-0.1237***
	(.0019)	(.0019)
1996.year	-0.1311***	-0.1295***
	(.0020)	(.0020)
1997.year	-0.1358***	-0.1340***
	(.0021)	(.0021)
1998.year	-0.1434***	-0.1415***
	(.0022)	(.0022)
1999.year	-0.1486***	-0.1465***
	(.0023)	(.0023)
2000.year	-0.1531***	-0.1506***
	(.0024)	(.0024)
2001.year	-0.1625***	-0.1596***
	(.0025)	(.0025)
2002.year	-0.1749***	-0.1715***
	(.0026)	(.0026)
2003.year	-0.1851***	-0.1812***
	(.0028)	(.0028)
2004.year	-0.1946***	-0.1902***
	(.0029)	(.0029)
2005.year	-0.2059***	-0.2011***
	(.0030)	(.0030)
2006.year	-0.2144***	-0.2092***
	(.0031)	(.0031)
Constant	0.3665***	0.3670***
	(.0039)	(.0039)
N	11,030,551	11,030,551
R-sq	0.0515	0.0515

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A15.vi. Regression *overall sample* without the age squared variable

Table A68: *Regressions (5) and (25), the impact technological age on the likelihood to change occupations, overall sample and overall sample without the age squared variable, full output table*

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample*, no age squared (25)
agriculture_fishing (1)	0.0068	0.0065
	(.0061)	(.0061)
miners_stone_workers (2)	0.0879***	0.0854***
	(.0126)	(.0126)
ceramic_glas (3)	-0.0694***	-0.0699***
	(.0153)	(.0154)
chemistry_synthetic_workers (4)	-0.0739***	-0.0747***
	(.0041)	(.0041)
paper_print (5)	-0.0369***	-0.0370***
	(.0054)	(.0054)
woodworking (6)	0.1704	0.1749
	(.1014)	(.1015)
metal_works (7)	-0.0138***	-0.0136***
	(.0035)	(.0035)
mechanics (8)	0.0472***	0.0459***
	(.0023)	(.0023)
electricians (9)	0.0598***	0.0580***
	(.0032)	(.0032)
assembly (10)	-0.0591***	-0.0601***
	(.0051)	(.0051)
textile_clothing_leather_fur (11)	0.1171***	0.1177***
	(.0116)	(.0116)
food (12)	0.0950***	0.0937***
	(.0074)	(.0074)
construction (13)	0.2608***	0.2605***
	(.0088)	(.0088)
interior_construction (14)	0.0506***	0.0499***
	(.0101)	(.0101)
carpenter (15)	0.0980***	0.0944***
	(.0073)	(.0073)
painter (16)	0.1099***	0.1080***
	(.0080)	(.0080)
product_testing (17)	-0.0989***	-0.0986***
	(.0057)	(.0057)
machinist (18)	0.0104	0.0129*
	(.0060)	(.0060)
engineer_math_chem (19)	0.0247***	0.0284***
	(.0029)	(.0029)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample*, no age squared (25)
technical_specilaist (20)	0.0418***	0.0440***
	(.0023)	(.0023)
goods_merchants (21)	0.0155***	0.0153***
	(.0029)	(.0029)
service_merchants (22)	-0.0063*	-0.0075**
	(.0027)	(.0027)
traffic (23)	-0.0163***	-0.0141***
	(.0033)	(.0033)
administration (24)	0.0194***	0.0199***
	(.0016)	(.0016)
regulatory_safety (25)	-0.0561***	-0.0522***
	(.0049)	(.0049)
writing_art (26)	0.0255***	0.0273***
	(.0056)	(.0057)
healthcare (27)	0.0520***	0.0502***
	(.0020)	(.0020)
social_education_science (28)	0.0251***	0.0257***
	(.0028)	(.0028)
age_sqared	0.0000***	
	.0000	
lvl_of_performance	-0.0152***	-0.0156***
	(.0005)	(.0005)
ln_formerjobs	-0.0184***	-0.0187***
	(.0002)	(.0002)
days_unemployed	-0.0000***	-0.0000***
	.0000	.0000
experience	0.0057***	0.0058***
	.0000	.0000
employment_change	-0.0099***	-0.0099***
	(.0005)	(.0005)
1.vocTrain	0	0
	(.)	(.)
2.vocTrain	-0.0975***	-0.0986***
	(.0011)	(.0011)
3.vocTrain	-0.0728***	-0.0737***
	(.0026)	(.0026)
4.vocTrain	-0.1450***	-0.1470***
	(.0019)	(.0019)
5.vocTrain	-0.2126***	-0.2148***
	(.0020)	(.0020)
1.industry	0	0
	(.)	(.)
2.industry	-0.0280***	-0.0284***
	(.0025)	(.0025)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample*, no age squared (25)
3.industry	-0.0316***	-0.0318***
	(.0023)	(.0023)
4.industry	-0.0443***	-0.0447***
	(.0023)	(.0023)
5.industry	-0.0114***	-0.0115***
	(.0023)	(.0023)
6.industry	0.0106***	0.0107***
	(.0031)	(.0031)
7.industry	-0.0121***	-0.0122***
	(.0023)	(.0023)
8.industry	-0.0021	-0.0021
	(.0022)	(.0022)
9.industry	-0.0283***	-0.0285***
	(.0024)	(.0024)
10.industry	-0.0015	-0.0016
	(.0022)	(.0022)
11.industry	-0.0243***	-0.0244***
	(.0024)	(.0024)
12.industry	-0.0363***	-0.0362***
	(.0024)	(.0024)
13.industry	-0.0433***	-0.0434***
	(.0024)	(.0024)
1.state	0	0
	(.)	(.)
2.state	-0.0114***	-0.0117***
	(.0022)	(.0022)
3.state	0.0022	0.0022
	(.0025)	(.0025)
4.state	-0.0051	-0.0052
	(.0034)	(.0034)
5.state	-0.0037	-0.0038
	(.0024)	(.0024)
6.state	-0.0066**	-0.0067**
	(.0025)	(.0025)
7.state	0.0063*	0.0064*
	(.0029)	(.0029)
8.state	-0.0033	-0.0033
	(.0025)	(.0025)
9.state	-0.0023	-0.0023
	(.0025)	(.0025)
10.state	-0.0005	-0.0005
	(.0045)	(.0045)
11.state	-0.0028	-0.0031
	(.0029)	(.0029)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample*, no age squared (25)
12.state	0.0134***	0.0133***
	(.0034)	(.0034)
13.state	0.0135**	0.0135**
	(.0042)	(.0042)
14.state	0.0141***	0.0140***
	(.0033)	(.0033)
15.state	0.0179***	0.0178***
	(.0037)	(.0037)
16.state	0.0182***	0.0182***
	(.0038)	(.0038)
1.KldB88	0	0
	(.)	(.)
2.KldB88	0.0034	0.0033
	(.0048)	(.0048)
3.KldB88	0.0185**	0.0182**
	(.0061)	(.0061)
4.KldB88	0.0097**	0.0095**
	(.0035)	(.0035)
5.KldB88	-0.0255***	-0.0262***
	(.0042)	(.0042)
6.KldB88	0.0280***	0.0276***
	(.0056)	(.0056)
7.KldB88	-0.0037	-0.0041
	(.0032)	(.0032)
8.KldB88	-0.0309***	-0.0308***
	(.0030)	(.0030)
9.KldB88	-0.0472***	-0.0469***
	(.0033)	(.0033)
10.KldB88	0.0217***	0.0215***
	(.0033)	(.0033)
11.KldB88	0.0027	0.0026
	(.0039)	(.0039)
12.KldB88	-0.0051	-0.0051
	(.0034)	(.0034)
13.KldB88	-0.0356***	-0.0359***
	(.0031)	(.0031)
14.KldB88	0.0119**	0.0117**
	(.0041)	(.0041)
15.KldB88	-0.0267***	-0.0264***
	(.0041)	(.0041)
16.KldB88	-0.0365***	-0.0365***
	(.0042)	(.0042)
17.KldB88	0.0336***	0.0332***
	(.0035)	(.0035)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample*	Occupation specific coefficients of log tech age *overall sample*, no age squared
	(5)	(25)
18.KldB88	-0.0113**	-0.0127**
	(.0039)	(.0039)
19.KldB88	-0.1131***	-0.1164***
	(.0038)	(.0038)
20.KldB88	-0.0838***	-0.0859***
	(.0033)	(.0033)
21.KldB88	-0.0526***	-0.0532***
	(.0031)	(.0031)
22.KldB88	-0.0875***	-0.0879***
	(.0036)	(.0036)
23.KldB88	-0.0439***	-0.0448***
	(.0029)	(.0029)
24.KldB88	-0.1117***	-0.1129***
	(.0030)	(.0030)
25.KldB88	-0.0253***	-0.0270***
	(.0041)	(.0041)
26.KldB88	-0.0891***	-0.0906***
	(.0050)	(.0050)
27.KldB88	-0.1598***	-0.1601***
	(.0036)	(.0036)
28.KldB88	-0.1014***	-0.1021***
	(.0037)	(.0037)
1979.year	0	0
	(.)	(.)
1980.year	-0.0069***	-0.0051***
	(.0006)	(.0006)
1981.year	-0.0191***	-0.0156***
	(.0007)	(.0006)
1982.year	-0.0326***	-0.0274***
	(.0007)	(.0006)
1983.year	-0.0427***	-0.0358***
	(.0008)	(.0007)
1984.year	-0.0495***	-0.0408***
	(.0008)	(.0007)
1985.year	-0.0548***	-0.0445***
	(.0009)	(.0007)
1986.year	-0.0600***	-0.0480***
	(.0010)	(.0008)
1987.year	-0.0681***	-0.0544***
	(.0011)	(.0008)
1988.year	-0.0754***	-0.0600***
	(.0012)	(.0008)
1989.year	-0.0782***	-0.0612***
	(.0013)	(.0009)

Dependent variable: occupation change in $t+1$	Occupation specific coefficients of log tech age *overall sample* (5)	Occupation specific coefficients of log tech age *overall sample*, no age squared (25)
1990.year	-0.0840***	-0.0653***
	(.0014)	(.0009)
1991.year	-0.0914***	-0.0710***
	(.0015)	(.0010)
1992.year	-0.0917***	-0.0699***
	(.0016)	(.0010)
1993.year	-0.1048***	-0.0813***
	(.0017)	(.0011)
1994.year	-0.1160***	-0.0909***
	(.0018)	(.0011)
1995.year	-0.1252***	-0.0984***
	(.0019)	(.0012)
1996.year	-0.1311***	-0.1027***
	(.0020)	(.0012)
1997.year	-0.1358***	-0.1058***
	(.0021)	(.0013)
1998.year	-0.1434***	-0.1119***
	(.0022)	(.0013)
1999.year	-0.1486***	-0.1154***
	(.0023)	(.0014)
2000.year	-0.1531***	-0.1183***
	(.0024)	(.0015)
2001.year	-0.1625***	-0.1261***
	(.0025)	(.0015)
2002.year	-0.1749***	-0.1368***
	(.0026)	(.0016)
2003.year	-0.1851***	-0.1454***
	(.0028)	(.0017)
2004.year	-0.1946***	-0.1533***
	(.0029)	(.0018)
2005.year	-0.2059***	-0.1630***
	(.0030)	(.0018)
2006.year	-0.2144***	-0.1698***
	(.0031)	(.0019)
Constant	0.3665***	0.3800***
	(.0039)	(.0038)
N	11,030,551	11,030,551
R-sq	0.0515	0.0514

*Note: Dependent variable is occupation change in period $t+1$. Robust standard errors are in parentheses. * significant at the 5 percent level, ** significant at the 1 percent level, *** significant at the 0.1 percent level.*

A16. Probability to leave an occupation multiplied by the average technological change per occupation

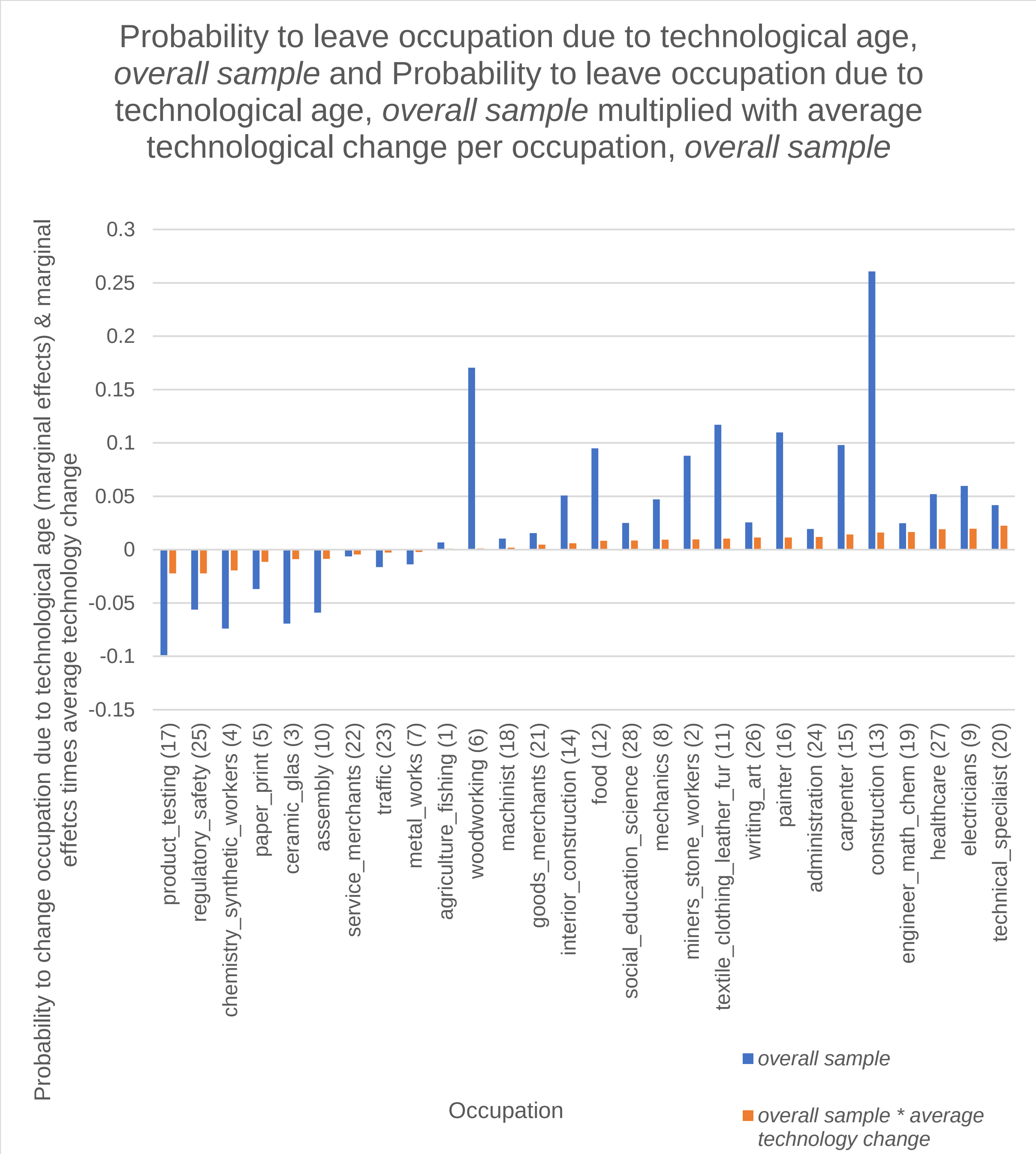

Figure A12: *Probability to leave occupation due to technological age, overall sample and Probability to leave occupation due to technological age, overall sample multiplied with average technological change per occupation, overall sample*

Note: Marginal effects of regression (5) and marginal effects of regression (5) multiplied by average technological change per occupation as taken from Table A3 to Table A6, ordered by size of marginal effects in regression (5) multiplied by average technological change per occupation.