

# Trends and cycles in U.S. job mobility

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## Abstract

Recent studies document a decline in U.S. labor-market fluidity from as early as the 1970s on. Making use of the *Annual Social and Economic* supplement to the *Current Population Survey*, I uncover a pronounced increase in job-to-job mobility from the 1970s to the 1990s, i.e. the annual share of continuously employed job-to-job movers rises from 5.9% of the labor force in 1975–1979 to 8.8% in 1995–1999. Job-to-job mobility exhibits a downward trend only since the turn of the millennium. In order to provide a formal economic interpretation, I additionally estimate the parameters of the random on-the-job search model. Furthermore, I document that job-to-job mobility has an unconditional correlation of  $-0.86$  with the unemployment rate at business-cycle frequencies in 1975–2017, varying by around 3 percentage points over the business cycle.

## KEYWORDS

business cycles, Current Population Survey, economic fluctuations, Fokker–Planck equation, job mobility, Kolmogorov forward equation, long-run trends, on-the-job search, productive efficiency, search and matching

## JEL CLASSIFICATION

J60; E32; C51

## 1 | INTRODUCTION

Recent studies stress the role of firms in explaining the trends in wage inequality: ‘It’s Where You Work: Increases in Earnings Dispersion across Establishments and Individuals in the U.S.’ (Barth et al., 2016) or ‘Firming Up Inequality’ (Song et al., 2019). Furthermore, the allocation of resources

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across economic activities is an important determinant of aggregate productivity. Hsieh and Klenow (2009) argue that aggregate productivity could rise by as much as 50% in China and 60% in India if resources were as efficiently allocated across firms as in the USA. Lentz and Mortensen (2008) find that the resource reallocation from less to more productive firms accounts for more than one-half of the aggregate growth in Denmark. Notably, a prominent and growing body of literature studies the sorting patterns among employees and employers in assignment and matching models (Chade et al., 2017).<sup>1</sup>

In contrast, the literature on long-run trends in worker mobility typically focuses on occupations, industries or regions. Kambourov and Manovskii (2008) document, at an annual frequency, a substantial rise in worker mobility across occupations and industries in the USA in 1968–1997. For instance, occupational (industry) mobility—measured by the fraction of currently employed individuals who report a change in occupations (industries)—increases from 16 (10) % to 20 (13) % at the three-digit classification level over the sample period. Studies of U.S. job mobility in the sense of interfirm mobility typically cover a limited time period only (Fallick & Fleischman, 2004).

In terms of methodology and data, this paper is most closely related to Blanchard and Diamond (1990) and Shimer (2005). Shimer (2005) stresses that, in an on-the-job search model, the procyclical job-finding rate of unemployed workers and the essentially acyclical separation rate (exit rate from employment) induce a procyclical pattern in job-to-job transitions. Making use of several coarse measures of job-to-job transitions, Shimer (2005) finds that the predicted business-cycle patterns are in line with the *Current Population Survey* (CPS) data in 1975–2003. However, Shimer (2005) does not study long-run trends. In particular, job-to-job transitions exhibit either a downward trend, no trend or an upward trend depending on the specific measure.

In the present paper, I make use of the *Annual Social and Economic* (ASEC) supplement to the CPS in order to study the evolution of job mobility in the USA in 1975–2017. I provide evidence that direct job mobility without intervening nonemployment spells, i.e. job-to-job mobility, and indirect job mobility with intervening nonemployment spells exhibit partly diverging trends. This finding is particularly intriguing in light of a growing body of literature that stresses the distinct economic implications of the different types of job mobility. Most notably, I document a surge in job-to-job mobility from the 1970s to the 1990s. Specifically, the annual share of continuously employed job-to-job movers rises from 5.9% of the labor force in 1975–1979 to 8.8% in 1995–1999. I note that time series of job-to-job mobility based on the monthly CPS start in 1994 (see, e.g. Moscarini & Thomsson, 2007). However, most of the increase in job-to-job mobility occurs before that year. Job-to-job mobility exhibits a downward trend since the turn of the millennium.

In order to provide a formal economic interpretation, I separately estimate the transition parameters of the canonical random on-the-job search model for the four fully covered business cycles over the sample period. My principal measure of job mobility is the ratio of the job-finding rate on the job to the transition rate into nonemployment—or, in general, the arrival rate of adverse shocks. A higher ratio induces, *ceteris paribus*, first-order stochastic dominance in the distribution of workers over

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<sup>1</sup>Stijepić (2017) integrates frictional labor markets with on-the-job search into an otherwise standard heterogeneous firm model of intra-industry trade, finding that trade liberalization raises the workers' returns to interfirm mobility by amplifying the disparities in revenue productivity between firms. Stijepić (2019) shows that, by weakening the competition between employers, a mean-preserving spread of the employers' productivity distribution decreases the share of the production output that the workers receive in the canonical on-the-job search model. Stijepić (2016) documents the comovement of the skill premium with the differential employer-size wage premium between high-skill and low-skill workers in U.S. manufacturing during the postwar era, suggesting that differences between large and small employers play an important role in explaining the recent increases in wage inequality.

jobs. In other words, the higher is this ratio, the more workers are in their preferred jobs. I estimate the ratio of the job-finding rate on the job to the transition rate into nonemployment to increase from 0.6 in 1975–1982 to 1.5 in 1993–2003. The ratio falls to 1.3 during the subsequent business cycle in 2004–2010.

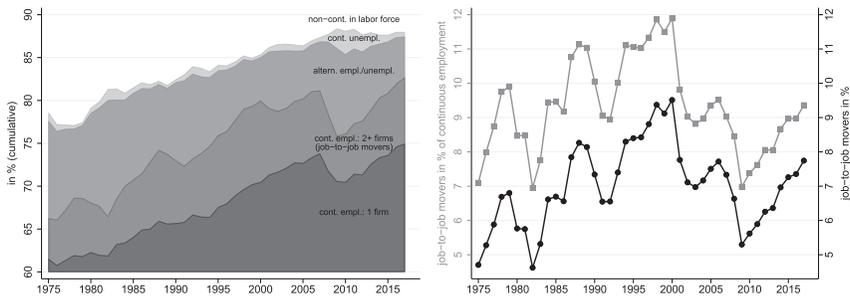
The fluctuations in job mobility at business-cycle frequencies are attracting sustained attention lately. For instance, Moscarini and Postel-Vinay (2016b, 2017) argue that employer–employer transitions are a better predictor of wage growth including the associated inflationary cost pressure than exits from unemployment. The present paper complements existing studies by providing a time series on job mobility that covers more than four decades and more than four business cycles. I document that job mobility as measured by the annual share of continuously employed job-to-job movers has an unconditional correlation of  $-0.86$  with the unemployment rate at business-cycle frequencies, varying by around 3 percentage points over the business cycle. Notably, the cyclical fall in job mobility during the Great Recession is not exceptionally large in comparison to all the recessions over the sample period according to the Hodrick–Prescott decomposition. The particularity of the Great Recession is rather the concurrence of a pronounced cyclical fall and a pronounced overall downward trend in job mobility, which already starts around the turn of the millennium.

This paper is structured as follows. A description of the ASEC data and summary statistics are in Section 2. I study the trends and cycles in job mobility in Section 3. In order to provide a formal interpretation for the presented time series, I estimate the transition parameters of the random on-the-job search model for the four fully covered business cycles in Section 4. Section 5 draws some conclusions. In the Appendix, I derive the likelihood function for the estimations in Section 4, making use of the Fokker–Planck formalism.

## 2 | THE ASEC DATA

The United States Bureau of the Census and the Bureau of Labor Statistics conduct the CPS jointly. The CPS covers a nationally representative sample of more than 60,000 households, who are interviewed monthly. For the following analysis, I specifically make use of the ASEC data as provided by Flood et al. (2018), which is based on the March supplement of the CPS. The March supplement of the CPS contains several questions relating to the respondent's employment in the preceding calendar year. In particular, the survey participants are asked to indicate how many weeks they were employed and how many weeks they were unemployed. Furthermore, the survey participants also report how many different employers they had during the preceding calendar year. Importantly, if a person worked for more than one employer simultaneously, then, the person is instructed to count it as only one employer. Therefore, the reported number of employers refers to job changes over the year, rather than to multiple jobs at one point in time. Finally, I measure the aggregate economic activity by the aggregate unemployment rate that is computed by the Bureau of Labor Statistics (series ID: LNU04000000).

I restrict my sample to survey participants ages 20–59, i.e. I exclude survey participants in their early and late stages of working life. Furthermore, I only study labor-force participants, i.e. survey participants who indicate having been employed, unemployed or looking for work for at least 1 week during the preceding calendar year. I employ sampling weights in all calculations in order to obtain representative statistics. Figure 1 decomposes, on the left-hand side, the sample into various sub-groups. I classify survey participants as continuously employed (unemployed) if they indicate having been employed (unemployed or looking for work) for at least 50 weeks during the preceding calendar year. Analogously, survey participants are continuously in the labor force if they indicate having been



**FIGURE 1** Sample decomposition into the subgroups defined in the main text on the left-hand side. Share of job-to-job movers in percent of all individuals (black line) and in percent of continuously employed individuals (gray line) on the right-hand side. Sample restricted to survey participants ages 20–59 who have been in the labor force for at least 1 week. Sampling weights employed in all calculations. Author's calculations based on the *Annual Social and Economic* (ASEC) data of the *Current Population Survey* as provided by Flood et al. (2018)

employed, unemployed or looking for work for at least 50 weeks during the preceding calendar year. Additionally, I distinguish continuously employed survey participants who indicate having had exactly one employer during the preceding calendar year from continuously employed survey participants who indicate having had at least two employers. Henceforth, I refer to the latter group as job-to-job movers.

The share of continuously employed individuals exhibits an upward trend over the sample period, reaching its maximum of 82.7% in 2017. In line with this pattern, the literature documents a secular decline in labor turnover over the last decades (see, e.g. Davis, 2008; Hyatt & Spletzer, 2013; Molloy et al., 2016; Fujita, 2018).<sup>2</sup> Continuously unemployed individuals typically represent less than 1.3% of all individuals who participate in the labor force except in 2009–2013. The Great Recession is marked by an unprecedented surge in the long-term unemployment rate to 2.7%. Notably, the literature stresses that the job-finding rate of unemployed workers predominantly explains the fluctuations in unemployment over the business cycle. Fluctuations in the exit rate from employment are essentially quantitatively irrelevant during the recent decades (see, e.g. Hall, 2006; Shimer, 2012).

Figure 1 depicts, on the right-hand side, the evolution of the share of job-to-job movers, i.e. continuously employed individuals with at least two employers over the year, in percent of all individuals who participate in the labor force and in percent of all continuously employed individuals. The two time series comove closely over the sample period, so that I focus, henceforth, on the share of movers in percent of all individuals who participate in the labor force. The average share of job-to-job movers over the sample period is 7.1%, ranging from 4.6% in 1982 to 9.5% in 2000. The share varies substantially even at an annual frequency, with an exceptional fall by 1.7 percentage points in 2000–2001. The share of job-to-job movers also exhibits clear long-run trends. In particular, the share rises from 5.9% of the labor force in 1975–1979 to 8.8% in 1995–1999. The turn of the millennium is marked by a trend reversal.

The number of continuously employed individuals with at least two employers over the year is a lower bound on the total number of job-to-job transitions during the year. In particular, it does not capture multiple job-to-job transitions of a single individual or job-to-job transitions of individuals who experience sizable nonemployment spells. To what extent the number of continuously employed

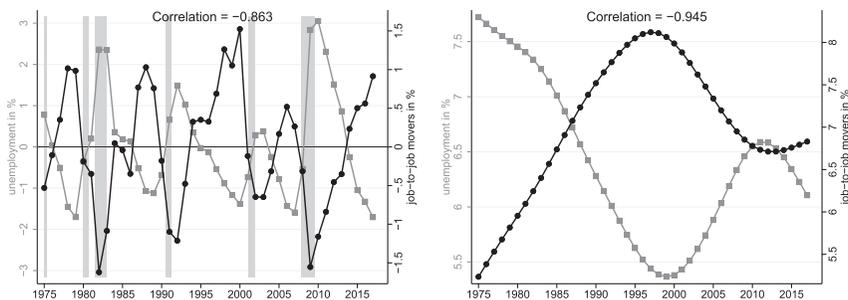
<sup>2</sup>Women are substantially more likely to be continuously in the labor force at the end of the sample period than at the beginning of the sample period. The share of survey participants who are 1–49 weeks in the labor force over the year decreases from 35% in 1975–1979 to 16% in 2010–2014 among women.

individuals with a least two employers over the year is a suitable measure of job mobility depends on the specific research question. The present paper focuses on the impact of job mobility on long-run productive efficiency (e.g. Lentz & Mortensen, 2008) and phenomena that are associated with the cyclical job ladder (e.g. Moscarini & Postel-Vinay, 2018). Notably, multiple job-to-job transitions over a relatively short period of time may rather reflect the person's struggle to find a suitable job than improvements in productive efficiency. Similarly, multiple job-to-job transitions are not necessarily an adequate indicator of the fierceness of the competition between firms for workers and the associated inflationary cost pressure. A similar reasoning holds for other excluded job-to-job transitions, e.g. job-to-job transitions of individuals who separate into unemployment shortly thereafter. In order to validate the share of continuously employed individuals with at least two employers over the year as a suitable measure of job mobility in the present context, I also estimate the transition parameters of the canonical on-the-job search model in Section 4.

### 3 | TRENDS AND CYCLES

In order to extract the trend and cycle components from the time series, I make use of the Hodrick–Prescott filter. Following Shimer (2012), I choose a high smoothing parameter of 390.625. When changing the observation frequency, Ravn and Uhlig (2002) argue that the smoothing parameter should be adjusted by multiplying it with the fourth power of the observation frequency ratio. Hence, a smoothing parameter of  $10^5$  at a quarterly frequency, which is used by Shimer (2012), implies a smoothing parameter of 390.625 at an annual frequency. I note that most related studies employ a high smoothing parameter (see, e.g. Moscarini & Postel-Vinay, 2012; Robin, 2011). Flaig (2015) shows that the Hodrick–Prescott filter with a high smoothing parameter is a good approximation of the optimal Wiener–Kolmogorov filter for autocorrelated cycle components.

Figure 2 depicts, on the left-hand side, the cycle components of the time series on continuously employed job-to-job movers and on aggregate unemployment. The shaded areas indicate NBER-dated contractions. Job-to-job mobility has an unconditional correlation of  $-0.86$  with the unemployment rate at business-cycle frequencies over the sample period, i.e. job mobility is procyclical. The fluctuations in job-to-job mobility over the business cycle are substantial with peak deviations of 1.5



**FIGURE 2** Decomposition of the time series on job-to-job movers and on aggregate unemployment into the cycle component (left-hand side) and the trend component (right-hand side) based on the Hodrick–Prescott filter with a smoothing parameter of 390.625. Sample restricted to survey participants ages 20–59 who have been in the labor force for at least 1 week. Sampling weights employed in all calculations. Author's calculations based on the *Annual Social and Economic* (ASEC) data of the *Current Population Survey* as provided by Flood et al. (2018) and on the aggregate unemployment rate of the Bureau of Labor Statistics (series ID: LNU0400000). Shaded areas indicate NBER-dated contractions

percentage points above the trend and of 1.6 percentage points below the trend. Recent studies of the fluctuations in worker and job flows include Fujita and Nakajima (2016). Barlevy (2002) argues that the reallocation of labor resources and improvements in productive efficiency occur rather during economic expansions than during economic contractions. Intuitively, employers create relatively fewer vacancies during recessions in response to less favorable conditions, so that workers have a more difficult time moving into those jobs for which they are best suited. Therefore, workers reallocate into their most productive uses more slowly and the average match quality declines.

Figure 2 displays, on the right-hand side, the trend components of the time series on continuously employed job-to-job movers and on aggregate unemployment. The trends in the two time series exhibit a pronounced correlation of  $-0.95$  over the sample period. All in all, job-to-job mobility and unemployment tend to be negatively correlated not only at business-cycle frequencies, but also at lower frequencies. Notably, I also find a negative correlation between measures of job mobility and unemployment across countries (Stijepić, 2018). Insofar as unemployment is an indicator of labor underutilization and job mobility is an indicator of productive efficiency, the correlation suggests that a higher degree of capacity utilization tends to be associated with a higher degree of productive efficiency. In other words, if a factor of production is scarce, it tends to be allocated across the different economic activities more efficiently.

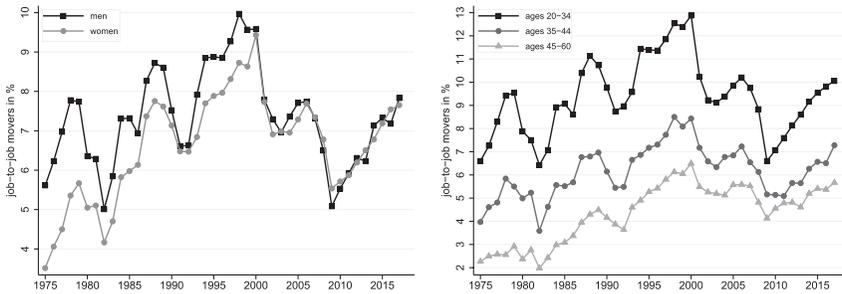
The trend component of job-to-job mobility is estimated to increase by more than 50% over the two initial decades, i.e. the share of continuously employed individuals with at least two employers over the year rises from 5.2% in 1975 to 8.0% in 1995. The following two decades are associated with a decrease in the trend component by 16%, i.e. the share of continuously employed job-to-job movers falls from 8.0% in 1995 to 6.8% in 2015. Notably, Beaudry et al. (2016) document a reversal in the demand for cognitive tasks and skills around the turn of the millennium.

Recent studies stress that the job ladder fails after the Great Recession (e.g. Moscarini & Postel-Vinay, 2016a). Notably, the cyclical fall in job mobility during the Great Recession is not exceptionally large in comparison to all the recessions over the sample period according to the Hodrick–Prescott decomposition. Specifically, the 1.6 percentage point below-trend decline in job-to-job mobility during the Great Recession is similar in magnitude to the 1.2–1.6 percentage point contractions during the recessions in the 1980s and 1990s. The particularity of the Great Recession is rather the concurrence of a pronounced cyclical fall and a pronounced overall downward trend in job mobility, which already starts around the turn of the millennium.

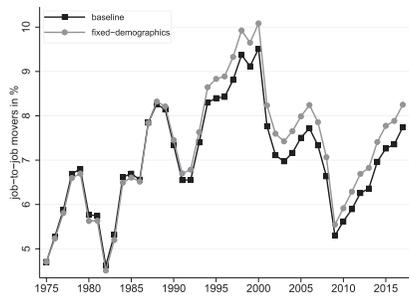
Figure 3 displays the evolution of job-to-job mobility by gender and by age. All in all, the share of continuously employed job-to-job movers exhibits qualitatively similar business-cycle patterns and trends among the demographic subgroups over the sample period. Nevertheless, there is substantial time-varying heterogeneity. In particular, the initial gender gap in job-to-job mobility of the 1970s narrows over the subsequent decades. The statistics do not suggest a sizable gender gap in job-to-job mobility in the 21st century.<sup>3</sup> Furthermore, the decline in job-to-job mobility during the first two recessions of the 21st century is most pronounced among the youngest survey participants, suggesting an uneven impact of the economic downturn.

I note that the increase in job mobility from the 1970s to the 1990s is even more pronounced when I reweight the sample to hold the demographic structure fixed. Specifically, I group the survey participants into 16 age–gender categories. I then rescale the sampling weights in each year, so that the shares of the 16 age–gender subgroups in any year match the shares in 1975. Figure 4 juxtaposes

<sup>3</sup>Notably, Hanushek et al. (2015) do not find a substantial gender gap in the wage returns to numeracy skills among full-time employed workers in their international study. However, the analysis of inactivity and unemployment suggests that the gender gap in the effects of skills is wider, the more comprehensive the studied sample is (Stijepić, 2020a).



**FIGURE 3** Share of job-to-job movers by gender (left-hand side) and by age (right-hand side). Sample restricted to survey participants ages 20–59 who have been in the labor force for at least 1 week. Sampling weights employed in all calculations. Author's calculations based on the *Annual Social and Economic* (ASEC) data of the *Current Population Survey* as provided by Flood et al. (2018)



**FIGURE 4** Original time series and fixed-demographics time series on the share of job-to-job movers. The weights for the fixed-demographics time series are rescaled for 16 age–gender subgroups in each year to match the respective shares in 1975. Sample restricted to survey participants ages 20–59 who have been in the labor force for at least 1 week. Sampling weights employed in all calculations. Author's calculations based on the *Annual Social and Economic* (ASEC) data of the *Current Population Survey* as provided by Flood et al. (2018)

the original time series on job mobility and the fixed-demographics time series on job mobility. The counterfactual time series suggests that the annual share of continuously employed job-to-job movers would have risen from 5.8% of the labor force in 1975–1979 to 9.3% in 1995–1999 in the absence of demographic change.

## 4 | A STRUCTURAL APPROACH

In order to provide a formal economic interpretation, I rely on the canonical (random) on-the-job search model (see, e.g. Burdett & Mortensen, 1998; Cahuc & Zylberberg, 2004). Rogerson et al. (2005) survey the literature on search-theoretic models of the labor market. In Section 4.1, I introduce the on-the-job search model and the likelihood function for the empirical analysis. A detailed derivation of the likelihood function is in the Appendix. In Section 4.2, I present the estimates of the transition parameters. In Section 4.3, I discuss the model predictions in light of the related literature.

## 4.1 | The likelihood function

A worker is either unemployed or employed. Both unemployed workers and employed workers receive job offers. The arrival rate is state dependent. Specifically, unemployed workers and employed workers obtain offers at rate  $\mu$  and at rate  $\lambda$ , respectively. Jobs are associated with fixed wage contracts,  $w$ . The wages are independent random draws from the wage-offer distribution  $F(\cdot)$ , i.e.,  $F(w)$  is the probability of receiving a wage offer no greater than  $w$ . The wage-offer distribution  $F(\cdot)$  is differentiable and the associated density function is  $f(\cdot)$ . Workers may only accept or reject a job offer. When information about a new job opportunity arises, employed workers quit their current job and move to the new job provided that the offered wage exceeds the current one. Without loss of generality, I consider an equilibrium in which unemployed workers accept any available job offer. Employed workers transition into unemployment at rate  $\delta$ . Furthermore, I introduce an activity margin in order to capture the important trends in the share of individuals who are non-continuously in the labor force. Specifically, workers exit the labor force at rate  $\rho$ . For each exiting unemployed person, another person enters the labor market through unemployment. For each exiting employed person, another person enters the labor market through employment, receiving an independent random draw from the wage-offer distribution  $F(\cdot)$ .

The probability of staying in the labor force over an entire period is  $e^{-\rho}$ . In the steady state, the flow of employed workers into unemployment,  $\delta Pr(empl.)$ , equals the flow of unemployed workers into employment,  $\mu Pr(unempl.)$ . Hence, the steady-state probability of being unemployed is  $\delta/(\delta + \mu)$ . I further distinguish workers who have been continuously unemployed over an entire period from unemployed workers who have not been continuously unemployed. The probability of being continuously unemployed over an entire period is  $\delta e^{-(\rho+\mu)}(\delta + \mu)^{-1}$ . Similarly, I also distinguish workers who have been continuously employed over an entire period from employed workers who have experienced a nonemployment spell. The probability of being continuously employed over an entire period is  $\mu e^{-(\rho+\delta)}(\delta + \mu)^{-1}$ .

Conditional on staying employed, workers transition to other firms at rate  $\lambda(1 - F(w))$ . Therefore, the conditional probability of staying at least one period with the current employer is  $e^{-\lambda(1 - F(w))}$ . I treat the wage as unobserved heterogeneity and integrate it out of the probability function. Specifically, let  $G(\cdot)$  denote the cross-sectional wage distribution. In the steady state, the outflow of workers into higher-paid jobs,  $\lambda(1 - F(w))G(w)Pr(empl.)$ , and into nonemployment,  $(\rho + \delta)G(w)Pr(empl.)$ , is equal to the inflow of workers from nonemployment,  $\mu F(w)Pr(unempl.) + \rho F(w)Pr(empl.)$ . Hence, the steady-state cross-sectional wage distribution is  $(\rho + \delta)F(w) / (\rho + \delta + \lambda(1 - F(w)))$ . Therefore, the conditional probability of staying at least one period with the current employer is  $\int_0^\infty e^{-\lambda(1 - F(w))} dG(w) = \int_0^1 (\rho + \delta)(\rho + \delta + \lambda)(\rho + \delta + \lambda(1 - x))^{-2} e^{-\lambda(1 - x)} dx$ , where the equality follows from a change of variables formula with  $x$  as  $F(\cdot)$ .

The likelihood for the empirical analysis is

$$\mathcal{L}_{\rho, \mu, \delta, \lambda} = \begin{cases} 1 - e^{-\rho} & \text{if non-cont. in labor force} \\ \frac{\delta e^{-(\rho+\mu)}}{(\delta + \mu)} & \text{if cont. unempl.} \\ \frac{\delta (e^{-\rho} - e^{-(\rho+\mu)})}{(\delta + \mu)} + \frac{\mu (e^{-\rho} - e^{-(\rho+\delta)})}{(\delta + \mu)} & \text{if altern. empl./unempl.} \\ \frac{\mu e^{-(\rho+\delta)}}{(\delta + \mu)} \int_0^1 \frac{(\rho + \delta)(\rho + \delta + \lambda)e^{-\lambda(1-x)}}{(\rho + \delta + \lambda(1-x))^2} dx & \text{if cont. empl. : 1 firm} \\ \frac{\mu e^{-(\rho+\delta)}}{(\delta + \mu)} \int_0^1 \left( 1 - \frac{(\rho + \delta)(\rho + \delta + \lambda)e^{-\lambda(1-x)}}{(\rho + \delta + \lambda(1-x))^2} \right) dx & \text{if cont. empl. : 2+ firms} \end{cases}, \quad (1)$$

where the transition parameters  $\rho$ ,  $\mu$ ,  $\delta$  and  $\lambda$  are to be estimated. Intuitively, the incidence of non-continuous labor-force participation determines the parameter  $\rho$ . The higher is the transition rate out of the labor force,  $\rho$ , the lower is the probability of observing a person who is continuously in the labor force. Information on the incidence of unemployment and the duration of unemployment spells among survey participants who are continuously in the labor force allows the identification of the parameters  $\mu$  and  $\delta$ . The higher is the job-finding rate of an unemployed person,  $\mu$ , the lower is, *ceteris paribus*, the probability of observing longer unemployment spells relative to shorter unemployment spells. Furthermore, the higher is the transition rate into unemployment,  $\delta$ , the lower is, *ceteris paribus*, the probability of observing an employed person. Information on the share of job-to-job movers is then sufficient to identify the job-finding rate on the job.

## 4.2 | The estimates of the transition parameters

In order to obtain estimates of the transition parameters, I separately maximize the likelihood function in Equation (1) for the four fully covered business cycles in 1975–1982, in 1983–1992, in 1993–2003 and in 2004–2010, respectively. Table 1 displays the maximum-likelihood per-annum estimates. All transition rates that govern the worker flows between employment and nonemployment, i.e.  $\rho$ ,  $\delta$  and  $\mu$ , are estimated to steadily decrease over the sample period. The average duration of a spell in the labor force,  $1/\rho$ , rises from 4.1 years in 1975–1982 to 7.4 years in 2004–2010. Conditional on staying in the labor force, the average duration of an employment spell (unemployment spell),  $1/\delta$  ( $1/\mu$ ), increases from 10.1 years (6.8 months) to 18.0 years (10.0 months) over the same period.

Table 1 also displays several job-mobility statistics: the job-finding rate on the job,  $\lambda$ , the average number of job offers per employment spell conditional on staying in the labor force,  $\lambda/\delta$ , the average number of job offers per employment spell,  $\lambda/(\rho + \delta)$ , and the average (instantaneous) job-to-job transition rate,  $\int_0^\infty \lambda(1 - F(w))dG(w)$ . Notably, all four job-mobility measures exhibit an inverted-‘U’ trend over the sample period. My preferred measure of job mobility is the ratio of the job-finding rate on the job to the transition rate into nonemployment,  $\lambda/(\rho + \delta)$ . It immediately follows from the steady-state expression for the cross-sectional wage distribution,  $G(w) = F(w) / (1 + (\lambda/(\rho + \delta))(1 - F(w)))$ , that a higher ratio induces first-order stochastic dominance in the distribution of workers over jobs.<sup>4</sup> In other words, the higher is this ratio, the more workers are in their preferred jobs. I estimate the average number of job offers per employment spell to increase from 0.6 in 1975–1982 to 1.5 in 1993–2003. The number falls to 1.3 during the subsequent business cycle in 2004–2010.

The ratio of the job-finding rate of unemployed workers to the separation rate into unemployment,  $\mu/\delta$ , coincides with the ratio of employed workers to unemployed workers in a steady-state equilibrium. Similar to the job-mobility statistics in Table 1, the ratio of the job-finding rate of unemployed workers to the separation rate into unemployment exhibits an inverted-‘U’ trend over the sample period. It rises from 18.0 in 1975–1982 to 28.6 in 1993–2003 before falling to 21.5 during the subsequent business cycle in 2004–2010. I note that the ratio of the job-finding rate of unemployed workers to the separation rate into unemployment,  $\mu/\delta$ , is inversely related to the steady-state unemployment rate,  $1/(1 + \mu/\delta)$ . Therefore, the model generates a negative correlation between the measures of

<sup>4</sup>Specifically, for  $\lambda/(\rho + \delta) > \lambda' / (\rho' + \delta') > 0$ , let  $G(\cdot)$  and  $G'(\cdot)$  denote the corresponding cross-sectional wage distributions. For a given sampling distribution,  $F(\cdot)$ , it follows that  $G(\cdot)$  first-order stochastically dominates  $G'(\cdot)$ , i.e.  $G(w) \leq G'(w)$  for all  $w \in [0, \infty)$  and  $G(w) < G'(w)$  for some  $w \in [0, \infty)$  (see Stijepić, 2020b).

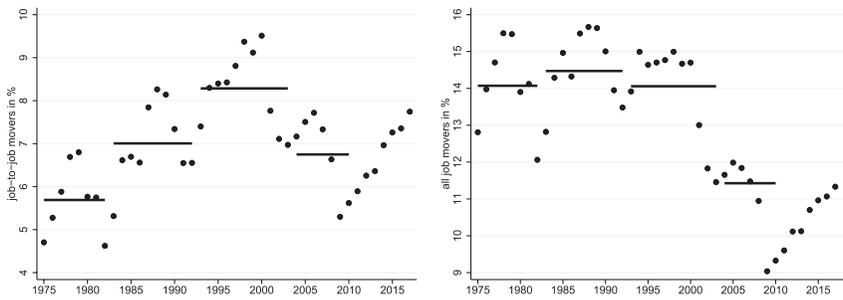
**TABLE 1** Maximum-likelihood per-annum estimates of the transition parameters in the random on-the-job search model

	1975–1982	1983–1992	1993–2003	2004–2010
Logarithmized risks				
$\ln(\rho)$	−1.4213*** (0.0030)	−1.6271*** (0.0028)	−1.8186*** (0.0028)	−2.0020*** (0.0035)
$\ln(\delta)$	−2.3161*** (0.0048)	−2.477*** (0.0044)	−2.8901*** (0.0048)	−2.8902*** (0.0052)
$\ln(\mu)$	0.5749*** (0.0067)	0.5649*** (0.0061)	0.4630*** (0.0063)	0.1774*** (0.0062)
$\ln(\lambda)$	−1.5380*** (0.0070)	−1.3101*** (0.0059)	−1.0953*** (0.0056)	−1.3740*** (0.0067)
Spell durations				
$1/\rho$	4.1424*** (0.0124)	5.0893*** (0.0145)	6.1634*** (0.0176)	7.4038*** (0.0260)
$1/\delta$	10.1360*** (0.0486)	11.9151*** (0.0524)	17.9949*** (0.0855)	17.997*** (0.0928)
$1/(\rho + \delta)$	2.9406*** (0.0075)	3.5661*** (0.0085)	4.5910*** (0.0112)	5.2458*** (0.0152)
$1/\mu$	0.5628*** (0.0038)	0.5684*** (0.0035)	0.6294*** (0.0040)	0.8374*** (0.0052)
$1/\lambda$	4.6554*** (0.0326)	3.7067*** (0.0220)	2.9900*** (0.0167)	3.9512*** (0.0264)
Further statistics				
$\mu/\delta$	18.0107*** (0.1082)	20.9618*** (0.1148)	28.5905*** (0.1617)	21.4912*** (0.1187)
$\lambda/\delta$	2.1772*** (0.0188)	3.2144*** (0.0244)	6.0185*** (0.0459)	4.5549*** (0.0398)
$\lambda/(\rho + \delta)$	0.6317*** (0.0048)	0.9621*** (0.0064)	1.5355*** (0.0099)	1.3276*** (0.0102)
$\int_0^\infty \lambda(1 - F(w))dG(w)$	0.0900*** (0.0005)	0.1050*** (0.0005)	0.1168*** (0.0005)	0.0917*** (0.0005)
Log-likelihood	−557,611	−712,317	−788,066	−592,468
Observations	525,335	692,859	824,515	643,715

Note: Sample restricted to survey participants ages 20–59 who have been in the labor force for at least 1 week. Sampling weights employed in all calculations. Delta-method standard errors in parentheses. Statistical significance at the 10%, 5% and 1% level denoted by \*, \*\* and \*\*\*, respectively.

Source: Author's calculations based on the *Annual Social and Economic* (ASEC) data of the *Current Population Survey* as provided by Flood et al. (2018).

job mobility and the unemployment rate over the sample period—in line with the right-hand side of Figure 2. All in all, the job-mobility estimates based on the canonical on-the-job search model are well in line with the job-mobility statistics in Section 3.



**FIGURE 5** Share of job-to-job movers (left-hand side) and of all job movers (right-hand side): model predictions (solid lines) and data points (dots). Sample restricted to survey participants ages 20–59 who have been in the labor force for at least 1 week. Sampling weights employed in all calculations. Author's calculations based on the *Annual Social and Economic (ASEC) data of the Current Population Survey* as provided by Flood et al. (2018)

### 4.3 | Discussion

Figure 5 depicts, on the left-hand side, the model predictions and the data points on the share of continuously employed job-to-job movers. By construction of the likelihood function in Equation (1), the model exactly matches the share of continuously employed job-to-job movers in the data: 5.7% in 1975–1982, 7.0% in 1983–1992, 8.3% in 1993–2003 and 6.7% in 2004–2010.<sup>5</sup> Another important statistic is the share of all job movers, i.e. the share of all survey participants who indicate having had at least two employers over the year. In order to obtain model predictions on the share of all job movers, I have to specify the work experience of individuals who (re)enter the labor force. I note that the likelihood function in Equation (1) does not depend on the biography of labor-force entrants. Specifically, I assume that 14.2% of all labor-force entrants have previous work experience with another employer in order to match the share of all job movers in the data in 1975–1982.

Figure 5 depicts, on the right-hand side, the model predictions and the data points on the share of all job movers. The model generates similar turnover rates as in the data: 14.1% versus 14.1% in 1975–1982, 14.5% versus 14.6% in 1983–1992, 14.1% versus 13.9% in 1993–2003 and 11.4% versus 10.9% in 2004–2010.<sup>6</sup> All in all, the model replicates (a) the surge in the share of continuously employed job-to-job movers and the relatively stable share of all job movers over the last decades of the 20th century and (b) the concurrent fall in both time series since the turn of the millennium.

How job mobility evolved over the last decades of the 20th century is controversial to some extent. Hyatt et al. (2018, p. 2171) state that ‘[d]ata sources on labor market fluidity do not show a consistent trend over this period. Depending on the series, employment reallocation rates may have increased, stayed roughly constant, or declined’. Davis (2008) argues that the incidence of unwelcome job loss

<sup>5</sup>Moscarini and Thomsson (2007) obtain a monthly job-to-job transition rate of 3.2% from the monthly CPS data, restricting their sample to employed male workers ages 16–64 in 1994–2006. The estimates in Table 1 imply a monthly job-to-job transition rate of 1.0% among employed workers in 1993–2003. Making use of the *Longitudinal Employer-Household Dynamics (LEHD)* data, Hyatt et al. (2018) find that 7.3% (5.0%) of workers separate from their main job and begin work at a new job either in the same quarter or the next in 2000 (in 2010). The estimates in Table 1 imply a quarterly job-to-job transition rate of 5.5% (4.2%) in 1993–2003 (in 2004–2010).

<sup>6</sup>I distinguish workers who have been unemployed for less than a year and workers who have been unemployed for at least a year in order to identify the job-finding rate of unemployed workers. Exploiting the variation in shorter unemployment spells tends to lead to higher estimates of the job-finding rate. Indeed, numerous studies have documented the negative duration dependence in the exit rate from unemployment in the USA (see, e.g. Elsby et al., 2013; Kaitz, 1970). Therefore, the model potentially underestimates the worker flows between unemployment and employment and, hence, the labor turnover across employers that is associated with intervening unemployment spells.

substantially decreased over the period, stressing that declining job stability as measured by, e.g. the median job tenure does not imply lower job security since most employment relationships do not end with an employer-initiated separation.<sup>7</sup> In contrast, the decline in job mobility since the turn of the millennium seems to be universal (see, e.g. Hyatt & Spletzer, 2013).

In line with the cited literature, all transition rates that govern the worker flows between employment and nonemployment in Table 1, i.e.  $\rho$ ,  $\delta$  and  $\mu$ , are estimated to decrease over the last decades of the 20th century, implying a decline in the indirect labor reallocation across firms that is associated with intervening nonemployment spells. In contrast, the job-finding rate on the job,  $\lambda$ , or the instantaneous job-to-job transition rate,  $\int_0^\infty \lambda(1 - F(w))dG(w)$ , in Table 1 are estimated to rise over the same period, implying an increase in the direct labor reallocation across firms that is not associated with intervening nonemployment spells. Therefore, the model is capable of generating a relatively stable level of total labor reallocation—as measured by the share of all job movers on the right-hand side of Figure 5—over the last decades of the 20th century. Furthermore, in line with the cited literature, all the transition rates in Table 1 are decreasing since the turn of the millennium, implying a universal decline in the labor reallocation across firms, i.e. the direct labor reallocation that is not associated with intervening nonemployment spells and the indirect labor reallocation that is associated with intervening nonemployment spells.<sup>8</sup>

## 5 | CONCLUSION

Making use of the ASEC supplement to the CPS, I study job mobility in the USA in 1975–2017, i.e. the sample period covers more than four decades and more than four business cycles. My principal measure of job mobility is the share of continuously employed individuals with at least two employers over the year. It is an adequate measure of job mobility for research questions relating to productive efficiency and the job ladder. In order to illustrate the validity of the job-mobility measure, I also estimate the transition parameters of the canonical on-the-job search model.

I document a surge in job mobility from the 1970s to the 1990s, i.e. the annual share of continuously employed job-to-job movers rises from 5.9% of the labor force in 1975–1979 to 8.8% in 1995–1999. I note that the increase in job mobility is even more pronounced when I reweight the sample to hold the demographic structure fixed. The counterfactual time series suggests that the annual share of continuously employed job-to-job movers would have risen from 5.8% of the labor force in 1975–1979 to 9.3% in 1995–1999 in the absence of demographic change. Job mobility exhibits a downward trend since the turn of the millennium.

At business-cycle frequencies, job mobility has an unconditional correlation of  $-0.86$  with the unemployment rate, varying by around 3 percentage points over the business cycle. Notably, the cyclical fall in job mobility during the Great Recession is not exceptionally large in comparison to all the recessions over the sample period according to the Hodrick–Prescott decomposition. The particularity of the Great Recession is rather the concurrence of a pronounced cyclical fall and a pronounced overall downward trend in job mobility, which already starts around the turn of the millennium.

<sup>7</sup>An unwelcome job loss is an employer-initiated separation that leads to unemployment, temporary or persistent drops in earnings and other significant costs.

<sup>8</sup>From the perspective of the on-the-job search model, the labor reallocation across firms with intervening nonemployment spells is not necessarily as closely related to productive efficiency as the labor reallocation without intervening nonemployment spells. A relevant question in this context is, e.g. whether creative destruction—in the sense that productivity increases are embodied in new jobs at the expense of old jobs—is associated with indirect or direct labor reallocation (see, e.g. Aghion & Howitt, 1994; Michau, 2013).

All in all, the present paper complements the literature on economic trends, suggesting concurrent trends in various economic time series: In line with the increase in worker mobility across occupations and industries over the last decades of the 20th century (Kambourov & Manovskii, 2008), I document an increase in job mobility over the same time period. In line with the trend reversal in the demand for cognitive tasks and skills around the turn of the millennium (Beaudry et al., 2016), I document a trend reversal in job mobility around the same time.

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## APPENDIX

## THE LIKELIHOOD FUNCTION

Let a person's state, denoted by  $s$ , be summarized by the vector  $(n, i, l, g)$ . The state variable  $g$  indicates a person's generation (or labor-force cycle), i.e. a person is either part of the initial generation of workers,  $g = 1$ , or a subsequent generation of workers,  $g = 2^+$ . A person's labor force status,  $l$ , is either employed,  $l = e$ , or unemployed,  $l = u$ . Furthermore, I distinguish workers who have been continuously employed over the entire sample period,  $e = e^+$ , from workers who are employed but have experienced a nonemployment spell,  $e = e^-$ . Similarly, there are workers who have been continuously unemployed over the entire sample period,  $u = u^+$ , and workers who are unemployed but have not been continuously unemployed,  $u = u^-$ . An employed person's income,  $i$ , is equal to the wage offered by the current employer,  $i = w$ . An unemployed person's sole source of income is home production,  $i = b$ . The fourth state variable  $n$  indicates the cumulative number of employers for which a person has worked. I do not track the number of employers for workers who are non-continuously employed or unemployed, i.e.  $n = l^-$  if  $l = e^-$  or  $l = u^-$ . Among the remaining workers, I distinguish individuals who have worked for at most one employer,  $n = 1^-$ , from individuals who have worked for at least two employers,  $n = 2^+$ .

As it is standard in continuous-time analysis, I introduce the concept of the infinitesimal time period  $dt > 0$ . The eventual modeling equations are those that emerge in the limit as  $dt$  approaches zero. The evolution over time of the person's state is described by the Markovian stochastic process  $s_{dt}(s)$ . In particular, a person's current state  $s$  determines the probability distribution of the person's state  $s_{dt}$  at the future point in time  $dt$ . Formally, a person's state evolves according to the stochastic differential equation

$$ds = \begin{cases} ((l^-, \omega, e^-, g) - s) dq_\mu + ((l^-, b, u^-, 2^+) - s) dq_\rho & \text{if } s = (n, b, u, g) \\ \mathbb{1}^*(\omega, s) ((l^-, \omega, e^-, g) - s) dq_\lambda & \text{if } s = (l^-, w, e^-, g) \\ + ((l^-, b, u^-, g) - s) dq_\delta + ((l^-, \omega, e^-, 2^+) - s) dq_\rho & \\ \mathbb{1}^*(\omega, s) ((2^+, \omega, e^+, 1) - s) dq_\lambda & \text{if } s = (n, w, e^+, 1) \\ + ((l^-, b, u^-, 1) - s) dq_\delta + ((l^-, \omega, e^-, 2^+) - s) dq_\rho & \end{cases}, \quad (\text{A1})$$

where  $ds = s_{dt} - s$ ,  $q_x$  is a Poisson process with an arrival rate of  $x$ , the wage offers  $\omega$  are random draws from the wage-offer distribution  $F(\cdot)$ , and the indicator function  $\mathbb{1}^*(\omega, s)$ , reflecting the optimal behavior of an employed person, equals one if  $\omega > w$  but is zero otherwise.<sup>9</sup>

The upper line on the right-hand side of Equation (A1) describes the evolution over time of an unemployed person's state. In the event of a job offer, i.e.  $dq_\mu = 1$ , the labor-force status changes from unemployed, either  $l = u^+$  or  $l = u^-$ , to non-continuously employed,  $l = e^-$ , the income rises from the value of home production,  $i = b$ , to the offered wage,  $i = \omega$ , and the indicator of the number of employers,  $n$ , remains at  $n = l^-$  for a person who is non-continuously unemployed,  $l = u^-$ , but changes from  $n = 1^-$  to  $n = l^-$  for a person who is continuously unemployed,  $l = u^+$ . In the event of an exit from the labor market, i.e.  $dq_\rho = 1$ , a person from a subsequent generation,  $g = 2^+$ , enters the labor market through unemployment, i.e.  $l = u^-$ ,  $i = b$  and  $n = l^-$ .

<sup>9</sup>Strictly speaking, the stochastic differential equation also incorporates the intergenerational changes in states and, hence, reflects the law of motion for a dynasty's state rather than a single person's state.

The middle line on the right-hand side of Equation (A1) describes the evolution of a non-continuously employed person's state. In the event of a job destruction, i.e.  $dq_\delta = 1$ , the labor-force status changes from non-continuously employed,  $l = e^-$ , to non-continuously unemployed,  $l = u^-$ , the income decreases from the received wage,  $i = w$ , to the value of home production,  $i = b$ , and the indicator of the number of employers remains at  $n = l^-$ . In the event of a job offer, i.e.  $dq_\lambda = 1$ , the associated term is only different from zero if  $\omega > w$ . In other words, the employed person's state remains unaltered in response to a wage offer if the wage offer,  $\omega$ , does not exceed the current wage,  $w$ . If  $dq_\lambda = 1$  and  $\omega > w$ , the wage income rises from  $w$  to  $\omega$ , but the labor-force status and the indicator of the number of employers remain at  $l = e^-$  and at  $n = l^-$ , respectively. In the event of an exit from the labor market, i.e.  $dq_\rho = 1$ , a person from a subsequent generation,  $g = 2^+$ , enters the labor market through employment, i.e.  $l = e^-$ ,  $i = \omega$  and  $n = l^-$ .

The lower line in Equation (A1) describes the evolution of a continuously employed person's state. The law of motion is similar to that for a non-continuously employed person's state except for the indicator of the cumulative number of employers. In the event of an accepted job offer, i.e.  $dq_\lambda = 1$  and  $\omega > w$ , the indicator of the cumulative number of employers changes from  $n = 1^-$  to  $n = 2^+$  for a person who has continuously worked for a single employer over the entire sample period. The indicator remains at  $n = 2^+$  for a person who has already experienced a job-to-job transition.

The probability function for the person's state at the future point in time  $dt$ ,  $p_{dt}(\cdot)$ , is a composite of mass and density functions, i.e.  $p_{dt}(n, i, l, g)$  is  $p_{dt}(1^-, b, u^+, 1)$  for  $s_{dt} = (1^-, b, u^+, 1)$ ,  $p_{dt}(l^-, b, u^-, 1)$  for  $s_{dt} = (l^-, b, u^-, 1)$ ,  $p_{dt}(l^-, b, u^-, 2^+)$  for  $s_{dt} = (l^-, b, u^-, 2^+)$ ,  $p_{dt}(l^-, w, e^-, 1)$  for  $s_{dt} = (l^-, w, e^-, 1)$ ,  $p_{dt}(l^-, w, e^-, 2^+)$  for  $s_{dt} = (l^-, w, e^-, 2^+)$ ,  $p_{dt}(1^-, w, e^+, 1)$  for  $s_{dt} = (1^-, w, e^+, 1)$  and  $p_{dt}(2^+, w, e^+, 1)$  for  $s_{dt} = (2^+, w, e^+, 1)$ . An expression for the probability function  $p_{dt}(\cdot)$  that is consistent with the stochastic process  $s_{dt}(\cdot)$  is not readily available. In order to derive the probability function, I rely on the Fokker–Planck formalism (see Bayer & Wälde, 2010; Stijepić, 2020). The remainder of this appendix is structured as follows. In Section A1, I derive a condition that characterizes the probability function  $p_{dt}(\cdot)$ . In Section A2, I construct the law of motion for the probability function  $p(\cdot)$  starting from that condition. In Section A3, I present a probability function  $p(\cdot)$  that is consistent with the derived law of motion.

## A1 | Probabilities and the probability function

Let the set  $A$  be a subset of the state space. The indicator function  $\mathbb{1}_A(x)$  equals one if  $x$  is an element of the set  $A$ , i.e.  $x \in A$ , but is zero otherwise. By construction, the probability that the person's state  $s_{dt}$  falls in the subset  $A$  at the future point in time  $dt$  is

$$\begin{aligned} Pr(s_{dt} \in A) = & \sum_{s \in \{(1^-, b, u^+, 1), (l^-, b, u^-, 1), (l^-, b, u^-, 2^+)\}} \mathbb{1}_A(s) p_{dt}(s) \\ & + \int_0^\infty \sum_{s \in \{(l^-, w, e^-, 1), (l^-, w, e^-, 2^+), (1^-, w, e^+, 1), (2^+, w, e^+, 1)\}} \mathbb{1}_A(s) p_{dt}(s) dw. \end{aligned} \quad (A2)$$

An alternative expression for the probability that the person's state  $s_{dt}$  falls in the subset  $A$  at the point in time  $dt$  is

$$\begin{aligned} Pr(s_{dt} \in A) = & \sum_{s \in \{(1^-, b, u^+, 1), (l^-, b, u^-, 1), (l^-, b, u^-, 2^+)\}} \mathbb{E}\{\mathbb{1}_A(s_{dt}(s))\} p(s) \\ & + \int_0^\infty \sum_{s \in \{(l^-, w, e^-, 1), (l^-, w, e^-, 2^+), (1^-, w, e^+, 1), (2^+, w, e^+, 1)\}} \mathbb{E}\{\mathbb{1}_A(s_{dt}(s))\} p(s) dw, \end{aligned} \quad (A3)$$

where the operator  $\mathbb{E}$  represents expectations. Intuitively,  $\mathbb{E} \{ \mathbb{1}_A (s_{dt}(s)) \}$  reflects the probability that the person's state  $s_{dt}$  falls in the subset  $A$  conditional on being  $s$  initially. The overall probability that the person's state  $s_{dt}$  falls in the subset  $A$  is the sum of all conditional probabilities weighted by the initial probability function  $p(s)$ .<sup>10</sup>

When is a probability function  $p_{dt}(\cdot)$  consistent with the law of motion for the person's state as postulated in Equation (A1)? Important in this context is that knowing a Borel measure on the open sets is sufficient to fully characterize the measure (see Stijepić, 2020). Therefore, the probability function  $p_{dt}(\cdot)$  is consistent with the law of motion for the person's state if the probability implied by the probability function  $p_{dt}(\cdot)$  in Equation (A2) coincides with that implied by the law of motion for the person's state in Equation (A3) for all open-set indicator functions. Equating Equation (A2) and Equation (A3) yields a recursive formula for the probability function  $p(\cdot)$ .

## A2 | The law of motion for the probability function

The (right) derivate of Equation (A2) with respect to time, i.e. for  $dt \rightarrow 0$ , is

$$\begin{aligned} \dot{Pr}(s \in A) = & \sum_{s \in \{(l^-, b, u^+, 1), (l^-, b, u^-, 1), (l^-, b, u^-, 2^+)\}} \mathbb{1}_A(s) \dot{p}(s) \\ & + \int_0^\infty \sum_{s \in \{(l^-, w, e^-, 1), (l^-, w, e^-, 2^+), (l^-, w, e^+, 1), (2^+, w, e^+, 1)\}} \mathbb{1}_A(s) \dot{p}(s) dw, \end{aligned} \quad (\text{A4})$$

where  $\dot{p}(s) = \lim_{dt \rightarrow 0} (p_{dt}(s) - p(s)) / dt$ . The (right) derivate of Equation (A3) with respect to time is

$$\begin{aligned} \dot{Pr}(s \in A) = & \sum_{s \in \{(l^-, b, u^+, 1), (l^-, b, u^-, 1), (l^-, b, u^-, 2^+)\}} \tilde{\phi}(s) p(s) \\ & + \int_0^\infty \sum_{s \in \{(l^-, w, e^-, 1), (l^-, w, e^-, 2^+), (l^-, w, e^+, 1), (2^+, w, e^+, 1)\}} \tilde{\phi}(s) p(s) dw, \end{aligned} \quad (\text{A5})$$

where the term  $\tilde{\phi}(s)$  is  $\mu \int_0^\infty \mathbb{1}_A(l^-, \omega, e^-, g) - \mathbb{1}_A(s) dF(\omega) + \rho (\mathbb{1}_A(l^-, b, u^-, 2^+) - \mathbb{1}_A(s))$  for  $s = (n, b, u, g)$ ,  $\lambda \int_w^\infty \mathbb{1}_A(l^-, \omega, e^-, g) - \mathbb{1}_A(s) dF(\omega) + \delta (\mathbb{1}_A(l^-, b, u^-, g) - \mathbb{1}_A(s)) + \rho \int_0^\infty \mathbb{1}_A(l^-, \omega, e^-, 2^+) - \mathbb{1}_A(s) dF(\omega)$  for  $s = (l^-, w, e^-, g)$  and  $\lambda \int_w^\infty \mathbb{1}_A(2^+, \omega, e^+, 1) - \mathbb{1}_A(s) dF(\omega) + \delta (\mathbb{1}_A(l^-, b, u^-, 1) - \mathbb{1}_A(s)) + \rho \int_0^\infty \mathbb{1}_A(l^-, \omega, e^-, 2^+) - \mathbb{1}_A(s) dF(\omega)$  for  $s = (n, w, e^+, 1)$ .

The expression on the right-hand side of Equation (A4) simply captures the changes in the probability function for the states in the subset  $A$ . Consider, e.g. an unemployed person who is not part of the initial generation of workers, i.e.  $s = (l^-, b, u^-, 2^+)$ . The probability of the state  $(l^-, b, u^-, 2^+)$  is  $p(l^-, b, u^-, 2^+)$ . At rate  $\mu$ , the state is expected to change from  $(l^-, b, u^-, 2^+)$  to  $(l^-, \omega, e^-, 2^+)$  in response to a job offer. The term  $\mathbb{1}_A(l^-, \omega, e^-, 2^+) - \mathbb{1}_A(l^-, b, u^-, 2^+)$  takes the value 1 if the initial state,  $(l^-, b, u^-, 2^+)$ , is not in the set  $A$  but the destination state,  $(l^-, \omega, e^-, 2^+)$ , is in the set  $A$ . It takes the value 0 if both the initial state and the destination state are in  $A$  or neither state is in  $A$ . It takes the value  $-1$  if the destination state is not in  $A$  but the initial state is in  $A$ . Therefore, the associated change in the probability  $Pr(s \in A)$  is either  $\mu p(l^-, b, u^-, 2^+)$ , 0 or  $-\mu p(l^-, b, u^-, 2^+)$ . Since the wage offers are random draws from the wage-offer distribution  $F(\cdot)$ , the change in the probability  $Pr(s \in A)$  that is associated with the initial state  $(l^-, b, u^-, 2^+)$  is the weighted average  $\mu \int_0^\infty \mathbb{1}_A(l^-, \omega, e^-, 2^+) - \mathbb{1}_A(l^-, b, u^-, 2^+) dF(\omega) p(l^-, b, u^-, 2^+)$ , which takes values between  $\mu p(l^-, b, u^-, 2^+)$  and  $-\mu p(l^-, b, u^-, 2^+)$ .

<sup>10</sup>In order to save on notation, I do not distinguish between simple and double parentheses, e.g.  $p(n, i, l, g)$  is equivalent to  $p((n, i, l, g))$ .

Equating Equations (A4) and (A5) yields

$$\sum_{\substack{s \in \{(1^-, b, u^+, 1), \\ (\Gamma^-, b, u^-, 1), (\Gamma^-, b, u^-, 2^+)\}}} \phi(s) \mathbb{1}_A(s) + \int_0^\infty \sum_{s \in \{(\Gamma^-, w, e^-, 1), (\Gamma^-, w, e^-, 2^+), \\ (1^-, w, e^+, 1), (2^+, w, e^+, 1)\}} \phi(s) \mathbb{1}_A(s) dw = 0, \quad (\text{A6})$$

where the term  $\phi(1^-, b, u^+, 1)$  equals  $\dot{p}(1^-, b, u^+, 1) + (\rho + \mu)p(1^-, b, u^+, 1)$ , the term  $\phi(\Gamma^-, b, u^-, 1)$  is equal to  $\dot{p}(\Gamma^-, b, u^-, 1) + (\rho + \mu)p(\Gamma^-, b, u^-, 1) - \delta \int_0^\infty p(2^+, w, e^+, 1) + p(1^-, w, e^+, 1) + p(\Gamma^-, w, e^-, 1) dw$ , the term  $\phi(\Gamma^-, b, u^-, 2^+)$  equals  $\dot{p}(\Gamma^-, b, u^-, 2^+) + (\rho + \mu)p(\Gamma^-, b, u^-, 2^+) - \delta \int_0^\infty p(\Gamma^-, w, e^-, 2^+) dw - \rho(p(1^-, b, u^+, 1) + p(\Gamma^-, b, u^-, 1) + p(\Gamma^-, b, u^-, 2^+))$ , the term  $\phi(\Gamma^-, w, e^-, 1)$  is  $\dot{p}(\Gamma^-, w, e^-, 1) + (\rho + \delta + \lambda(1 - F(w)))p(\Gamma^-, w, e^-, 1) - \mu f(w)(p(1^-, b, u^+, 1) + p(\Gamma^-, b, u^-, 1)) - \lambda f(w) \int_0^w p(\Gamma^-, w, e^-, 1) d\omega$ , the term  $\phi(\Gamma^-, w, e^-, 2^+)$  is equal to  $\dot{p}(\Gamma^-, w, e^-, 2^+) + (\rho + \delta + \lambda(1 - F(w)))p(\Gamma^-, w, e^-, 2^+) - \mu f(w)p(\Gamma^-, b, u^-, 2^+) - \lambda f(w) \int_0^w p(\Gamma^-, \omega, e^-, 2^+) d\omega - \rho f(w) \int_0^\infty p(2^+, \omega, e^+, 1) + p(1^-, \omega, e^+, 1) + p(\Gamma^-, \omega, e^-, 1) + p(\Gamma^-, \omega, e^-, 2^+) d\omega$ , the term  $\phi(1^-, w, e^+, 1)$  is equal to  $\dot{p}(1^-, w, e^+, 1) + (\rho + \delta + \lambda(1 - F(w)))p(1^-, w, e^+, 1)$  and the term  $\phi(2^+, w, e^+, 1)$  is equal to  $\dot{p}(2^+, w, e^+, 1) + (\rho + \delta + \lambda(1 - F(w)))p(2^+, w, e^+, 1) - \lambda f(w) \int_0^w p(2^+, \omega, e^+, 1) + p(1^-, \omega, e^+, 1) d\omega$ . In order to obtain Equation (A6) from Equations (A4) and (A5), it suffices to change the order of integration. In particular, I note that  $\int_0^\infty \lambda \int_w^\infty \mathbb{1}_A(\Gamma^-, \omega, e^-, 1) dF(\omega) p(\Gamma^-, w, e^-, 1) dw$  is equal to  $\int_0^\infty \lambda \mathbb{1}_A(\Gamma^-, \omega, e^-, 1) f(\omega) \int_0^\omega p(\Gamma^-, w, e^-, 1) dwd\omega$ .

Equation (A6) is obviously satisfied for any open-set indicator function if the  $\phi$ -terms vanish. The resulting equations, i.e.  $\phi(n, i, l, g) = 0$  for all  $n, i, l$  and  $g$ , are the so-called Fokker–Planck equations or Kolmogorov forward equations for the probability function  $p(\cdot)$ , describing the evolution over time of that probability function:

$$\dot{p}(1^-, b, u^+, 1) = -(\rho + \mu)p(1^-, b, u^+, 1) \quad (\text{A7})$$

$$\begin{aligned} \dot{p}(\Gamma^-, b, u^-, 1) &= -(\rho + \mu)p(\Gamma^-, b, u^-, 1) \\ + \delta \int_0^\infty p(2^+, w, e^+, 1) + p(1^-, w, e^+, 1) + p(\Gamma^-, w, e^-, 1) dw \end{aligned} \quad (\text{A8})$$

$$\begin{aligned} \dot{p}(\Gamma^-, b, u^-, 2^+) &= -(\rho + \mu)p(\Gamma^-, b, u^-, 2^+) + \delta \int_0^\infty p(\Gamma^-, w, e^-, 2^+) dw \\ + \rho(p(1^-, b, u^+, 1) + p(\Gamma^-, b, u^-, 1) + p(\Gamma^-, b, u^-, 2^+)) \end{aligned} \quad (\text{A9})$$

$$\begin{aligned} \dot{p}(\Gamma^-, w, e^-, 1) &= -(\rho + \delta + \lambda(1 - F(w)))p(\Gamma^-, w, e^-, 1) \\ + \mu f(w)(p(1^-, b, u^+, 1) + p(\Gamma^-, b, u^-, 1)) + \lambda f(w) \int_0^w p(\Gamma^-, \omega, e^-, 1) d\omega \end{aligned} \quad (\text{A10})$$

$$\begin{aligned} \dot{p}(\Gamma^-, w, e^-, 2^+) &= -(\rho + \delta + \lambda(1 - F(w)))p(\Gamma^-, w, e^-, 2^+) \\ + \mu f(w)p(\Gamma^-, b, u^-, 2^+) + \lambda f(w) \int_0^w p(\Gamma^-, \omega, e^-, 2^+) d\omega \\ + \rho f(w) \int_0^\infty p(2^+, \omega, e^+, 1) + p(1^-, \omega, e^+, 1) + p(\Gamma^-, \omega, e^-, 1) + p(\Gamma^-, \omega, e^-, 2^+) d\omega \end{aligned} \quad (\text{A11})$$

$$\dot{p}(1^-, w, e^+, 1) = -(\rho + \delta + \lambda(1 - F(w)))p(1^-, w, e^+, 1) \quad (\text{A12})$$

$$\begin{aligned} \dot{p}(2^+, w, e^+, 1) = & -(\rho + \delta + \lambda(1 - F(w)))p(2^+, w, e^+, 1) \\ & + \lambda f(w) \int_0^w p(2^+, \omega, e^+, 1) + p(1^-, \omega, e^+, 1) d\omega \end{aligned} \quad (\text{A13})$$

By construction, the Fokker–Planck equations are consistent with the law of motion for a person's state in Equation (A1). In the present application, the Fokker–Planck equations are a system of ordinary differential equations and integro-differential equations.

The law of motion in Equations (A7)–(A13) for the probability function  $p(\cdot)$  is intuitive. For instance, consider the state of a person who has been continuously working for a single employer at a wage of  $w$ , i.e.  $s = (1^-, w, e^+, 1)$ . Equation (A12) describes the evolution over time of the associated density  $p(1^-, w, e^+, 1)$ . The density decreases over time at rate  $-\lambda(1 - F(w))p(1^-, w, e^+, 1)$  in response to higher-wage job offers, at rate  $-\delta p(1^-, w, e^+, 1)$  in response to job destruction and at rate  $-\rho p(1^-, w, e^+, 1)$  in response to exits from the labor force.

### A3 | The probability function

In order to derive the likelihood function in the main text, I impose several steady-state conditions:  $p_\tau(1^-, b, u^+, 1) + p_\tau(l^-, b, u^-, 1) + p_\tau(l^-, b, u^-, 2^+) = \delta / (\delta + \mu) \quad \forall \tau \in [0, t]$  and  $p_\tau(2^+, w, e^+, 1) + p_\tau(1^-, w, e^+, 1) + p_\tau(l^-, w, e^-, 1) + p_\tau(l^-, w, e^-, 2^+) = \mu(\rho + \delta)(\rho + \delta + \lambda)f(w)(\delta + \mu)^{-1}(\rho + \delta + \lambda(1 - F(w)))^{-2} \quad \forall w \forall \tau \in [0, t]$ . The implied initial conditions are  $p_0(1^-, b, u^+, 1) = \delta / (\delta + \mu)$ ,  $p_0(1^-, w, e^+, 1) = \mu(\rho + \delta)(\rho + \delta + \lambda)f(w)(\delta + \mu)^{-1}(\rho + \delta + \lambda(1 - F(w)))^{-2}$  and  $p_0(n, i, l, g) = 0$  otherwise.

After integrating the wages out from the probability function  $p(l^-, w, e^-, 2^+)$ , the law of motion in Equation (A11) simplifies to  $\int_0^\infty \dot{p}(l^-, w, e^-, 2^+) dw = -(\rho + \delta) \int_0^\infty p(l^-, w, e^-, 2^+) dw + \mu p(l^-, b, u^-, 2^+) + \rho \mu (\delta + \mu)^{-1}$ , where  $\int_0^\infty F(w)p(l^-, w, e^-, 2^+) + f(w) \int_0^w p(l^-, \omega, e^-, 2^+) d\omega dw = \int_0^\infty p(l^-, w, e^-, 2^+) dw$  by the integration-by-parts formula and  $\int_0^\infty p(2^+, \omega, e^+, 1) + p(1^-, \omega, e^+, 1) + p(l^-, \omega, e^-, 1) + p(l^-, \omega, e^-, 2^+) d\omega = \mu / (\delta + \mu)$  by the steady-state conditions. Therefore, with Equation (A9) and the steady-state condition  $p(1^-, b, u^+, 1) + p(l^-, b, u^-, 1) + p(l^-, b, u^-, 2^+) = \delta / (\delta + \mu)$ , the law of motion for the probability of being non-continuously in the labor force is  $\dot{p}(l^-, b, u^-, 2^+) + \int_0^\infty \dot{p}(l^-, w, e^-, 2^+) dw = -\rho(p(l^-, b, u^-, 2^+) + \int_0^\infty p(l^-, w, e^-, 2^+) dw) + \rho$ , which is a linear differential equation. With the initial condition  $p_0(l^-, b, u^-, 2^+) + \int_0^\infty p_0(l^-, w, e^-, 2^+) dw = 0$ , it admits the solution  $p_t(l^-, b, u^-, 2^+) + \int_0^\infty p_t(l^-, w, e^-, 2^+) dw = 1 - e^{-\rho t}$ . The law of motion in Equation (A9) is a linear differential equation as well, where  $\int_0^\infty p_t(l^-, w, e^-, 2^+) dw = 1 - e^{-\rho t} - p_t(l^-, b, u^-, 2^+)$ . With the initial condition  $p_0(l^-, b, u^-, 2^+) = 0$ , it admits the solution  $p_t(l^-, b, u^-, 2^+) = \delta(1 - e^{-\rho t})(\delta + \mu)^{-1}$ .

The law of motion for the probability of being continuously unemployed in Equation (A7) is a linear differential equation. It admits, with the initial condition  $p_0(1^-, b, u^+, 1) = \delta(\delta + \mu)^{-1}$ , the solution  $p_t(1^-, b, u^+, 1) = \delta e^{-(\rho + \mu)t}(\delta + \mu)^{-1}$ . The law of motion in Equation (A8) is also a linear differential equation, where  $\int_0^\infty p(2^+, w, e^+, 1) + p(1^-, w, e^+, 1) + p(l^-, w, e^-, 1) dw = \mu e^{-\rho t}(\delta + \mu)^{-1}$ . With the initial condition  $p_0(l^-, b, u^-, 1) = 0$ , it admits the solution  $p_t(l^-, b, u^-, 1) = \delta(e^{-\rho t} - e^{-(\rho + \mu)t})(\delta + \mu)^{-1}$ . After integrating the wages out from the probability function  $p(l^-, w, e^-, 1)$ , the law of motion in Equation (A10) is  $\int_0^\infty \dot{p}(l^-, w, e^-, 1) dw = -(\rho + \delta) \int_0^\infty p(l^-, w, e^-, 1) dw + \mu(p(1^-, b, u^+, 1) + p(l^-, b, u^-, 1))$ , which is a linear differential equation. With the initial condition  $\int_0^\infty p_0(l^-, w, e^-, 1) dw = 0$ , it admits the solution  $\int_0^\infty p_t(l^-, w, e^-, 1) dw = \mu(e^{-\rho t} - e^{-(\rho + \delta)t})(\delta + \mu)^{-1}$ . The law of motion for the probability of having been continuously working for a single employer at a wage of  $w$  in Equation (A12) is a linear differential equation. With the

initial condition  $p_0(1^-, w, e^+, 1) = \mu(\rho + \delta)(\rho + \delta + \lambda)f(w)(\delta + \mu)^{-1}(\rho + \delta + \lambda(1 - F(w)))^{-2}$ , it admits the solution  $p_t(1^-, w, e^+, 1) = \mu(\rho + \delta)(\rho + \delta + \lambda)f(w)(\delta + \mu)^{-1}(\rho + \delta + \lambda(1 - F(w)))^{-2} e^{-(\rho + \delta + \lambda(1 - F(w)))t}$ . After integrating the wages out from the probability function, the probability is  $\int_0^\infty p_t(1^-, w, e^+, 1) dw = \mu(\rho + \delta)(\rho + \delta + \lambda)(\delta + \mu)^{-1} \int_0^1 (\rho + \delta + \lambda(1 - x))^{-2} e^{-(\rho + \delta + \lambda(1 - x))t} dx$ .

Therefore, the probability function  $p_t(n, l, g)$  is

$$p_t(n, l, g) = \begin{cases} \frac{\delta e^{-(\rho + \mu)t}}{(\delta + \mu)} & \text{if } n = 1^- \wedge l = u^+ \wedge g = 1 \\ \frac{\delta(e^{-\rho t} - e^{-(\rho + \mu)t})}{(\delta + \mu)} & \text{if } n = l^- \wedge l = u^- \wedge g = 1 \\ \frac{\delta(1 - e^{-\rho t})}{(\delta + \mu)} & \text{if } n = l^- \wedge l = u^- \wedge g = 2^+ \\ \frac{\mu(e^{-\rho t} - e^{-(\rho + \delta)t})}{(\delta + \mu)} & \text{if } n = l^- \wedge l = e^- \wedge g = 1 \\ \frac{\mu(1 - e^{-\rho t})}{(\delta + \mu)} & \text{if } n = l^- \wedge l = e^- \wedge g = 2^+ \\ \frac{\mu e^{-(\rho + \delta)t}}{(\delta + \mu)} \int_0^1 \frac{(\rho + \delta)(\rho + \delta + \lambda)e^{-\lambda(1-x)t}}{(\rho + \delta + \lambda(1-x))^2} dx & \text{if } n = 1^- \wedge l = e^+ \wedge g = 1 \\ \frac{\mu e^{-(\rho + \delta)t}}{(\delta + \mu)} \int_0^1 1 - \frac{(\rho + \delta)(\rho + \delta + \lambda)e^{-\lambda(1-x)t}}{(\rho + \delta + \lambda(1-x))^2} dx & \text{if } n = 2^+ \wedge l = e^+ \wedge g = 1 \end{cases}, \quad (A14)$$

where the lower line follows from  $p_t(1^-, u^+, 1) + p_t(l^-, u^-, 1) + p_t(l^-, u^-, 2^+) + p_t(l^-, e^-, 1) + p_t(l^-, e^-, 2^+) + p_t(1^-, e^+, 1) + p_t(2^+, e^+, 1) = 1$ . Provided that a law of large numbers applies (see Duffie & Sun, 2012; He et al., 2017; Sun, 2006), the function  $p_t(n, l, g)$  also reflects the probabilities of observing a person with the respective state variables in a random sample from the population.