Firm and Worker Dynamics in an Aging Labor Market

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Abstract

I assess the impact of an aging labor force on business dynamism, labor market fluidity and economic growth. The analysis embeds endogenous growth through creative destruction in an equilibrium job ladder model, highlighting feedback between the extent of mismatch in the labor market and incentives to innovate. I calibrate the model to aggregate reallocation rates and show that the theory replicates life cycle firm and worker dynamics in the data. The model implies that labor force aging over the last 30 years in the US explains 40–50 percent of the decline in job and worker reallocation and has reduced annual economic growth by 0.3 percentage points. Using cross-state variation and instrumenting for the incidence of aging using lagged age shares, I find additional empirical support for the prediction of large effects of aging on dynamism and growth.

Keywords: Demographic structure; Endogenous growth; Creative destruction; Declining dynamism; Job ladder; Occupational choice

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1 Introduction

The aging of the labor force is an important phenomenon in many advanced countries. Because older individuals are less mobile, less innovative and less willing to take risk, labor force aging has potentially far-reaching implications for a range of economic outcomes and policy.[1] In this paper, I focus on the impact of an aging US labor force on the operation of the US labor market, and argue that it has lead to a significant decline in firm and worker dynamics and has had a negative effect on economic growth.

I make three contributions: First, I propose a theory that links business dynamism, labor market fluidity and economic growth to the age composition of the labor force. The model embeds endogenous growth through creative destruction in an equilibrium job ladder model, highlighting two-way feedback between the extent of mismatch in the labor market and incentives to innovate. Second, I apply the theory to the case of the US over the last 30 years in order to provide a quantitative assessment of the impact of aging on dynamism. To that end, I calibrate the model to match aggregate firm and worker reallocation rates, and demonstrate that the model correctly predicts life-cycle firm and worker dynamics in the data, providing confidence in the theory. Subsequently, I evaluate the impact of a change in the age composition of the labor force on four key measures of dynamism—job reallocation, firm turnover, worker flows (employment-to-unemployment and job-to-job mobility) and economic growth—and show that the observed aging of the labor force has contributed to significant declines in each. Third, I use cross-state variation in the incidence of aging and an instrumental variables strategy to lend support to the model's prediction of large effects of aging on dynamism and growth.

I develop a model of joint firm and worker life-cycle dynamics that embeds endogenous growth through creative destruction in an equilibrium job ladder model. Firms are subject to idiosyncratic and permanent shocks to their productivity and hire individuals in a frictional labor market. Individuals search for better employment opportunities both on and off the job and choose when to become entrepreneurs over their life-cycle. A central element of models of creative destruction is that entry of new, more productive entrepreneurs pushes out the least productive incumbent firms, giving rise to a life-cycle of firms. Firms enter small, a few survive and grow

[1] See Jones (2010) for evidence that older people are less innovative, and Josef et al. (2016) for evidence that older individuals are less willing to take risk. Earlier research has found that, among other things, aging may have significant consequences for unemployment (Shimer, 2001), business cycles (Jaimovich and Siu, 2009), the returns to experience (Jeong et al., 2015), monetary policy (Wong, 2016), and fiscal policy (Mcgrattan and Prescott, 2017).

large, but eventually all firms are replaced by more productive, new entrants. A key feature of job ladder models is a notion of endogenous labor market mismatch—the equilibrium rate at which individuals move up and down the ladder affects how well individuals are paired with firms. Combining these two properties, individuals' rank on the job ladder gradually deteriorates as their firms fall behind the market leader over time. Through a time-consuming process of on the job search, individuals may offset the negative drift in the relative productivity of their firm by moving to better firms.

In line with robust empirical patterns, older individuals in the model are less likely to both become entrepreneurs and move between employers. This results from older individuals having had more time to find a good match for their skills, thereby raising their opportunity cost of a move. As a consequence, by tilting the workforce toward older, less mobile parts of the population, aging reduces business dynamism and labor market fluidity through a composition effect. Furthermore, the less mobile recruitment pool in the older economy dissuades firms from creating jobs and entrepreneurs from entering by increasing the effective cost of hiring. Finally, aging reduces dynamism through the following equilibrium mechanism. A decline in the entry rate due to the effects highlighted above slows the process of creative destruction. Consequently, individuals do not fall behind on the job ladder as quickly, resulting in less labor market mismatch. This reduces the job-to-job mobility hazard, which discourages entry by again raising the effective cost of recruiting and by increasing the opportunity cost of entry, since potential entrepreneurs would have to sacrifice a more lucrative employment position in order to enter. It also reduces the employment-to-unemployment hazard as fewer firms exit.

I calibrate the model to match salient features of firm and worker dynamics in the US Census Bureau's Business Dynamic Statistics (BDS) and Survey of Income and Program Participation (SIPP). The model fits the data well. On the firm side, I target average firm size, employment shares by firm size, employment shares by firm size among entrant firms, the aggregate entry and exit rate, and estimates of the contribution of firm selection to economic growth. The model predicts as an endogenous equilibrium outcome life-cycle firm dynamics that match the data, including the extent to which older firms are larger, less likely to exit and have lower job reallocation rates conditional on remaining. This suggests that the proposed theory of random growth, firm selection and labor market frictions captures key forces driving life-cycle firm dynamics. On the worker side, I target the aggregate employment-to-unemployment and job-to-job mobility hazards, and show that the model generates life-cycle profiles of these mobility rates that closely mimic their empirical counterparts as an endogenous equilibrium outcome. This supports the mechanisms proposed by the model as key drivers of life-cycle worker mobility patterns.

I next use the model to quantify the effect of aging on dynamism. To that end, I change the age composition in the model holding all other parameters fixed, and evaluate its effect on the long-run balanced growth path equilibrium. The model implies that the aging of the US labor force has led to quantitatively important declines in business dynamism, labor market fluidity and economic growth. In particular, it explains 39 percent of the decline in job reallocation in the data, 56 percent of the decline in firm turnover, 36 percent of the decline in the employment-to-unemployment hazard, and 48 percent of the decline in the job-to-job mobility hazard. In line with the data, I show that a standard shift-share analysis on model-generated data suggests a much smaller role of aging. I conclude that aging has had important equilibrium effects on dynamism, which such a simple accounting exercise does not capture.

A key question raised by Davis and Haltiwanger (2014) is whether the slowdown in dynamism is cause for concern. The model suggests two opposing effects of aging. On one hand, annual economic growth falls by 0.27 percentage points in response to aging, driven by less creative destruction. On the other hand, the lower unemployment rate and the shift of individuals up the job ladder give rise to a 5.5 percent positive level effect on net output. In addition, reduced dynamism is associated with a lower risk of becoming unemployed and more generally lower income volatility of individuals. This highlights that although the less dynamic environment is worrisome for the long-run macroeconomic performance of the economy, it is associated with fewer adverse shocks at the micro level. In the long run, the growth effect outweighs the level effect so that discounted net output falls by four percent across the two balanced growth path equilibria.

To provide additional support for the hypothesis that aging has had important effects on dynamism, I exploit variation in the magnitude and timing of aging across US states from 1978 to 2014. I correlate the age composition of a state with various measures of dynamism, controlling for state fixed effects, year effects and growth in state real output per worker. To partly address concerns that workers of different ages may move differentially across states in response to temporary variation in dynamism, I instrument for the current share of older individuals in a state using lagged age shares. I also consider the same regression framework with growth in state real GDP per worker as the outcome variable.

In line with the predictions of the model, the cross-state variation suggests a quantitatively important covariation between aging and dynamism. A higher share of older people is associated with lower dynamism across a range of measures of establishment, firm and worker dynamics, as well as growth in real GDP per worker. This is not primarily the consequence of changes in sectoral composition or state economic policy that are correlated with aging, and I typically find more pronounced results when I instrument for the current age composition using lagged age shares. To the extent that the cross-state variation reflects a causal relationship and is informative about the effect of aging at the national level, the estimates would suggest that aging accounts for 40–50 percent of the large declines in firm and worker dynamism since 1986 and just over a one percentage point decline in growth in real GDP per worker.[2] This lends support to the predicted large equilibrium effects of aging in the model.

Related literature. My paper is related to three strands of the literature. First, as in the original Burdett and Mortensen (1998) model and in more recent work by Borovickova (2016), Lise and Robin (2017) and Moscarini and Postel-Vinay (2013, 2016), I study a random search environment in which firms hire multiple workers and workers search on the job.[3] I contribute to this literature a model in which firms are subject to idiosyncratic shocks and enter and exit, individuals are characterized by a life-cycle and choose when to become entrepreneurs, and growth is endogenous.

Second, I relate to a literature on growth in an environment with labor marker frictions. Aghion and Howitt (1994) and Mortensen and Pissarides (1998) find that job creation may increase in the rate of economic growth. I reach a similar conclusion, but emphasize a different mechanism behind this outcome, namely a congestion externality in the labor market in the spirit of Diamond (1982). This arises from the introduction of on the job search. Michau (2013) and Miyamoto and Takahashi (2011) also consider models with growth and on the job search to study the relationship between growth and unemployment, but abstract from a life-cycle of individuals and an entrepreneurial choice, and model growth as exogenous.[4] None of the above papers discusses the

[2] The estimated relationship between the share of older individuals and the job-to-job mobility hazard, however, is not statistically significant when I instrument for the current share of older workers. As I discuss in greater detail later, data on job-to-job mobility are only available for a much more limited number of years, which may account for the lack of statistical significance. Maestas et al. (2016) also find that growth is negatively correlated with aging across US states using a somewhat different methodology.

[3] Kaas and Kircher (2015) and Schaal (2016) construct directed search models with multi-worker firms, but abstract from an entrepreneurship decision and growth.

[4] The relationship between growth and unemployment is the subject of a large literature, including Postel-Vinay (2002), Hornstein et al. (2007), Michelacci and Lopez-Salido (2007), Pissarides and Vallanti (2007), and Prat (2007).

feedback between labor market mismatch and growth that I emphasize.[5]

Third, a recent and rapidly expanding empirical literature studies changes in US dynamism. Davis and Haltiwanger (2014) provide a comprehensive overview of the declines using a variety of data sources and discuss potential factors behind them.[6] Davis et al. (2010) link the decline in unemployment inflows to declines in job destruction and find that the latter accounts for 28 percent of the secular decline in the former from 1982 to 2005 using cross-industry variation (and 55 percent since 1990). Pugsley and Sahin (2015) suggest that while firm entry has fallen substantially over the past decades, incumbent dynamics have remained the same conditional on firm age. Decker et al. (2017a), on the other hand, show that dynamism has fallen also within firm age groups. Furthermore, they argue that the decline in job reallocation is not due to more benign productivity shocks but due to a weaker employment response of firms to shocks. Molloy et al. (2016) discuss potential explanations behind the broad-based declines in job and worker turnover since the early 1980s, but without a formal model. Finally, Decker et al. (2017b) suggest that the decline in reallocation has led to weaker economic growth.

Fewer papers provide a structural model of the declines.[7] In a recent working paper, Karahan et al. (2016) argue that with anticipation effects, the slowdown in labor supply growth over this period can account for up to 25 percent of the decline in start-up activity. My paper differs in two key dimensions. First, we focus on different mechanisms. While they evaluate the importance of labor supply growth on the start-up rate through the lens of a Hopenhayn (1992) industry equilibrium model of firm dynamics, I study the effect of the age composition through a new model of firm and worker dynamics. In my empirical work, I show in a joint framework that both mechanisms receive support in the data, and hence I view our papers as offering complementary explanations for the large decline in dynamism (in fact, even adding both of our mechanisms, an important share of the declines remains unexplained). Second, my model and empirical analysis

These papers abstract from on the job search and endogenous growth.

[5]A vast literature studies endogenous growth absent frictional labor markets, including Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992); Luttmer (2007), Lucas and Moll (2014), Perla and Tonetti (2014) and Sampson (2016).

[6]To mention a few papers, Shimer (2012) notes the decline in the employment-to-unemployment hazard in the Current Population Survey (CPS), Hyatt (2015) discusses the decline in job-to-job mobility in the CPS, and Bosler and Petrosky-Nadeau (2016) discuss the decline in job-to-job mobility in the SIPP (see also Hyatt and Spletzer, 2013, and Decker et al., 2016).

[7]See also Kaplan and Schulhofer-Wohl (2017), who provide a structural model of the decline in interstate migration, Liang et al. (2016), who seek to understand the inverse u-shaped entrepreneurship entry rate over the life-cycle as well as the fact that younger countries have higher entrepreneurship entry rates conditional on age, and Shimer (2001), who studies the equilibrium effect of the age composition on unemployment in a frictional labor market.

speak to changes in a range of outcomes over and above the start-up rate that is the focus of their paper, including worker mobility and economic growth. I find that across US states, long-run declines in the various measures of dynamism are strongly positively correlated with each other, which motivates me to develop a unified framework to evaluate the declines.[8]

To summarize, the main contribution of this paper is to develop a theory of joint firm and worker life-cycle dynamics that incorporates entry and exit of firms, on the job search, an entrepreneurship decision, and endogenous growth, and apply the theory to quantitatively assess the impact of aging over the last 30 years in the US on business dynamism, labor market fluidity and economic growth.

Outline. The next section summarizes four sets of facts that motivate my study. Section 3 develops a theory of joint firm and worker dynamics to interpret these facts, and Section 4 outlines the balanced growth path equilibrium of the model. Section 5 brings the model to the data to show that it replicates life-cycle firm and worker dynamics as non-targeted equilibrium outcomes, providing confidence in the theory. Section 6 uses the model to quantify the equilibrium effect of aging. Section 7 provides empirical support for the hypothesis using cross-state variation over this period in aging and dynamism. Finally, Section 8 concludes.

2 Motivating Facts

The analysis of this paper is motivated by four sets of facts. Although each of these has been documented separately by various authors, it is important for my subsequent analysis to establish them in a consistent manner. Hence, I construct these facts using a combination of data from the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), the BDS, the CPS and the SIPP. I briefly report the findings of this analysis here, and provide the details in Appendix B. As I define variables in a standard fashion, I refer to Appendix A for the definitions.

First, firm and establishment dynamics have declined substantially over this period, as initially noted by Davis et al. (2006). The employment-weighted turnover rate of firms has declined by 38 percent since 1986. This is driven by declines in both entry and exit; in particular these have declined by 46 percent and 27 percent, respectively. The overall job reallocation rate has declined

[8] From an accounting perspective, some of this positive correlation is expected. I show in Appendix B that a strong correlation in long-run secular declines between measures remains after taking out the component that is mechanical.

by 28 percent. Although roughly half of this is accounted for by the decline in turnover, the other half reflects a fall in job reallocation for incumbents. The declines are not accounted for by sectoral shifts.

Second, worker flows have fallen significantly. The employment-to-unemployment (EU) hazard has declined by 30–40 percent and the job-to-job (JJ) hazard has declined by 25–30 percent since 1986. In contrast, the unemployment-to-employment (UE) hazard showed little evidence of a secular decline until the Great Recession, when it fell substantially. Given that the UE hazard is volatile at business cycle frequencies, it is plausible that the recent decline at least in part is a business cycle phenomenon rather than a secular trend (at the time of this writing, the UE hazard has almost recovered to its pre-Great Recession level).

Third, although uncertainty surrounds the exact magnitude of the slowdown, an emerging consensus finds that trend economic growth has declined (Fernald, 2014). Growth in real GDP per labor force participant has fallen from an average of 2.6 percent per year in 1984–1988 to 1.7 percent in 2012–2016.[9]

Fourth, the US labor force has aged substantially over this period. The share of the labor force that is 40 years of age and older achieved a trough in the mid-1980s and has increased by 15 percentage points since 1986. This is not driven by differential trends in labor force participation by age.

The next section develops an equilibrium job ladder model with endogenous growth driven by creative destruction in order to understand these facts. I return to interpret them through the lens of the structural model in Section 6.

3 A Job Ladder with Creative Destruction

This section outlines an equilibrium model of the labor market with the following three features. First, firm productive heterogeneity combined with on-the-job search give rise to a job ladder that individuals gradually climb with time in the market. Second, the presence of a factor in fixed supply implies that entry of new, more productive firms pushes out the least productive incumbent firms, i.e. creative destruction. Third, individuals face a life cycle.

[9] Although I report growth in GDP per labor force participant for reasons that will become clear in the model, the drop is similar to the decline in growth in real GDP per hour, which has declined from 1.8 percent annually in 1984–1988 to 0.7 percent annually in 2012–2016.

3.1 Environment

Time is continuous and there are no aggregate shocks. The economy consists of a unit mass of ex-ante identical individuals, who can be one of A ages.[10] They enter the economy as age one and move stochastically to the next age at rate $\kappa(a)$. Once an individual reaches the oldest age group, she dies at rate $\kappa(A)$ and is replaced by her offspring. I assume that individuals are perfectly altruistic in the sense that they care as much about their offspring as themselves. That is, one can think of the economy as being populated by a unit continuum of dynasties.[11] Dynasties value an expected stream of consumption discounted at rate $\tilde{\rho}$, including a consumption equivalent flow value of leisure $B(t)$ enjoyed during periods of unemployment,[12]

$$\mathbb{E}_t \int_t^{\infty} \exp(-\tilde{\rho}(\tau - t)) \left(c(\tau) + B(\tau)\right) d\tau$$

Firms. At each point in time, a positive mass of firms is heterogeneous in current productivity, Z, and employment level. When a firm first hires an individual, they draw a match productivity, $x \in \{x_b, x_g\}$ with $x_b < 1 < x_g$ normalized such that $\mathbb{E}(x) = 1$. Match productivity is independent across matches, fixed for the duration of the match, and learned by both parties at rate ψ.[13] The purpose of introducing learning is quantitative: it generates worker flows over and above job flows and it allows the model to quantitatively match life cycle mobility.[14] Qualitatively, my results would hold without this ingredient of the model.

Total output of a firm with productivity Z and e_b, e_g and e_u of bad, good and unknown quality matches, respectively, is given by

$$y\left(Z, e_b, e_g, e_u\right) = Z(x_b e_b + x_g e_g + e_u)$$

[10] The quantitative section typically considers the case of $A = 3$.

[11] With a varying probability of death over the life cycle, the effective discount rate would in general vary. Assuming that individuals are perfectly altruistic with respect to their offspring simplifies by avoiding this.

[12] For reasons that will become clear, I allow $B(t)$ to vary over time to ensure the existence of a balanced growth path.

[13] In a discrete time setting, Pries (2004) shows how this outcome can be microfounded by assuming that match output is observed with noise, $x + \varepsilon(t)$, where the noise is uniform $\varepsilon(t) \sim U(-\xi, \xi)$. If observed output is less than $x_g - \xi$, the match infers that it must be low productive, since this outcome can never happen if it were high productive. A symmetric argument implies that a match learns that it is high productive when output is greater than $x_b + \xi$. Any observation of match output in $[x_g - \xi, x_b + \xi]$ is equally likely regardless of underlying match quality and the match learns nothing. Consequently, the rate of learning equals $\psi = (x_g - x_b)/2\xi$.

[14] Without learning, the JJ hazard declines over the life cycle as individuals climb a job ladder, but this mechanism is not strong enough to match the decline in the data. Similarly, the EU hazard falls with age as individuals climb away from firms close to the separation threshold, but again this force only matches part of the empirical decline. Nagypál (2007) finds that such learning is economically significant.

where a law of large numbers implies that the productivity of the mass e_u of matches deterministically equals one. Firm productivity evolves according to a geometric Brownian motion,

$$dZ(t) = \sigma Z(t) dW(t)$$

where $dW(t)$ is the standard Wiener process. These productivity shocks could be viewed as reflecting either TFP shocks, demand shocks or a combination of both.[15]

To expand its workforce, a firm needs to pay a fixed cost $\tilde{r}(t)$ associated with employing a marketing specialist to create new employment opportunities at the firm, as well as a variable cost per vacancy posted. Specifically, a mass v of vacancies comes at strictly convex flow cost,

$$c_v(v,t) = c_v \underline{Z}(t) \frac{v^{1+\eta}}{1+\eta}, \qquad\qquad c_v, \eta > 0$$

where $\underline{Z}(t)$ denotes the lowest productivity of firms seeking to hire at time t. I thus follow a large strand of the literature in assuming that costs grow at the rate of the economy to ensure a balanced growth path (BGP).[16] The total flow cost of posting v vacancies is hence $\tilde{r}(t) + c_v(v,t)$. Following the literature, unfilled vacancies are assumed to be forsaken, and if the firm stops paying the fixed cost it permanently exits the hiring market.

Entrepreneurial choice. At rate $\gamma(a)$, an individual gets the opportunity to start a business. I allow this to differ by age to match the inverse u-shaped entrepreneurship entry hazard with age in the data.[17] To pursue the opportunity, she has to pay a cost $c_e \underline{Z}(t)$, where $c_e \sim \Omega$, and quit her job if she is employed. Subsequently, she draws an initial productivity Z from probability density function (pdf) $\tilde{\phi}$,

$$\tilde{\phi}(Z,t) = \zeta \underline{Z}(t) Z^{-(\zeta+1)}$$

[15] One could add a drift to incumbent growth without impacting the results of this paper, which I hence abstract from for simplicity. I later calibrate parameters to match estimates of the contribution of selection to economic growth.

[16] See for instance Romer (1990), Aghion and Howitt (1992), Aghion and Howitt (1994), Kortum (1997), Mortensen and Pissarides (1998), and chapters 13–14 of Acemoglu (2011). Bollard et al. (2016) discuss how such an assumption can be microfounded by viewing costs to be in terms of time, but for simplicity, I follow the standard in the literature and simply assume that such costs grow at the rate of the economy. Although several normalizations are possible, including for instance relative to mean wages, it is particularly tractable to normalize to the lowest productivity.

[17] The literature has yet to reach a definite answer as to why the entry rate behaves as it does over the life cycle, with proposed explanations including changes in risk-aversion, the utility cost of working hard, the ability to conduct critical thinking, and creativity (see for instance Liang et al., 2016, and Acemoglu et al., 2017, for recent papers in economics and Ruth and Birren, 1985, and Ryan et al., 2000, for contributions in other fields). In light of such ambiguity, I take a reduced-form approach. I note that all other life cycle patterns in the model are the outcomes of endogenous, optimal choices.

I note two things: First, by linking the distribution of innovations to that of incumbent firms, the model features an externality in the sense that entrants benefit from the successes of previous firms. This allows the model to attain perpetual economic growth. Second, innovation on average takes place far from the frontier, in contrast to first-generation models of creative destruction (Aghion and Howitt, 1992; Grossman and Helpman, 1991). My approach follows recent contributions such as Luttmer (2012) and is motivated by the empirical observation that entrants typically enter small with a high exit probability. Only through a sequence of favorable shocks does an entrant grow large. Section 5 shows that this assumption is consistent with key patterns in the data including exit rates by firm age, firm size by firm age, and employment shares by firm age.[18]

Having come up with an idea (i.e. a productivity Z) for a new business, an innovating individual offers it to a mutual fund at a take-it-or-leave-it price and returns to the labor market as unemployed.

Mutual fund. A mutual fund owns all ideas in the economy and purchases ideas from innovating individuals at a price such that the individual captures the entire surplus. In this sense, the model is similar to Romer (1990)'s seminal model in which an intermediate goods producer purchases blueprints from a research and development-producing sector such that the inventor captures the entire surplus. This assumption simplifies the problem by avoiding the age of the founder as a state in the firm's problem (and hence also in the employed individual's problem).[19] Following the creative destruction literature, I assume a factor in fixed supply, which implies that entry of new, more productive firms pushes out the least productive incumbents. That is, it gives rise to creative destruction.[20] Specifically, I assume that the mutual fund possesses M marketing specialists that it rents out to firms in a perfectly competitive market. The mutual fund distributes

[18] Appendix B provides evidence of no systematic differences in post-entry firm performance by age of the founder.

[19] An earlier version of this paper had owner entrepreneurs who bequeathed their firms to their offspring when they died, which complicated the problem but did not change results. I note in particular with respect to this that flows into entrepreneurship are an order of magnitude lower than EU flows in both the model and the data. The mutual fund is assumed to own firms but not be involved in their day-to-day operational decisions (specifically, firms do not internalize the negative effect their vacancy posting decisions have on other firms).

[20] For instance, Klette and Kortum (2004) assume a fixed number of goods and Perla and Tonetti (2014) a fixed stock of entrepreneurs. I think about this fixed factor as marketing specialists, but alternative interpretations may be human or physical capital, land or real estate. I note with respect to this assumption that average firm size has only increased slightly over this period in the data, which the model matches under this assumption (due to a decline in the unemployment rate). I have also considered a version with a fixed cost instead of a fixed factor, but this delivers a counterfactually large change in the number of firms (and an even larger effect of aging). Hence, I assume a fixed factor in the spirit of the creative destruction literature.

any profits that it makes as lump sum transfers to all individuals.[21]

Search and matching. Since individuals who come up with an idea for a business immediately sell it, an individual may at any point in time be either employed or unemployed. Unemployed and employed individuals search with the same efficiency, which I normalize to one.[22] Following the literature, I assume that if firms post an aggregate amount of vacancies $\bar{v}$, the total number of matches that takes place equals $\chi \bar{v}^{\alpha}$, where χ is aggregate matching efficiency and α is the elasticity of matches with respect to vacancies. Denote by λ the rate at which an individual meets an open vacancy and by q the rate at which an open vacancy contacts an individual,

$$\lambda = \chi \bar{v}^{\alpha}, \qquad \text{and} \qquad q = \chi \bar{v}^{\alpha - 1} \tag{1}$$

Wage setting. Firms and individuals bargain over the proceeds of their match following Cahuc et al. (2006). When an unemployed individual meets a firm, the two engage in an alternating offers game as in Rubinstein (1982). This results in the individual receiving the full value of unemployment, plus a share β of the difference between the value of the match and the value of unemployment. If an employed individual meets a new firm, the current and new firm engage in Bertrand competition for the individual's services. This competition is won by the firm with the higher valuation of the match, and the second highest value becomes the individual's outside option in a new alternating offers game with the winning firm. The individual either switches to the new employer and gets the full value of her previous match plus a share β of the differential value between the two matches, or stays with her current employer but potentially gets an updated contract that delivers the value of the poaching match plus a share β of the differential surplus. The latter is subject to the individual not being worse off by receiving an outside offer.

The bargaining protocol pins down the split of the surplus, but not the timing of payments. Lacking a satisfactory model of when individuals get paid, I follow Postel-Vinay and Turon (2010) in assuming that individuals are paid a fixed wage in place until either party has a credible threat to force renegotiation. I show in Appendix E that this assumption delivers a process for wages that matches wage dynamics in the data.

[21]Given that utility is linear, such transfers have no impact on incentives; hence, I abstract from them when formulating the individual's problem for simplicity.

[22]See Faberman et al. (2017) for evidence that although employed workers spend less time searching, this is countered by the fact that they receive more offers per unit of time searched.

In an environment with subsequent shocks, situations may arise in which, for a given payment scheme, one party of a match has a credible threat to abandon the match although there are mutual gains from preserving it. To avoid such bilaterally inefficient separations, I allow for renegotiation in these cases. Specifically, I assume that this delivers an updated contract such that the party that initiated the renegotiation is indifferent between leaving the match and remaining.

4 Equilibrium with Balanced Growth

This section considers a BGP equilibrium in which the lower threshold, $\underline{Z}(t)$, and the price of a marketing specialist, $\tilde{r}(t)$, grow at endogenous rate μ, while incumbent firm productivity remains fixed in expectation. It is convenient to instead study a transformed economy where the lower threshold and the price of a marketing specialist are constant. To that end, I normalize all relevant variables by the lower threshold, $\underline{Z}(t)$. Denote by z the log of transformed firm productivity, $z = \log(Z(t)/\underline{Z}(t))$, by r the transformed price of a marketing specialist, by $\phi(z)$ the transformed log innovation distribution, and by ρ the difference between the subjective discount rate and the growth rate, $\tilde{\rho} - \mu$. In the transformed economy, firm productivity drifts downward at rate μ while r is constant. Finally, I assume that the flow value of unemployment equals $B(t) = b\underline{Z}(t)$.[23]

4.1 Value functions

I now formulate the three key Bellman equations that characterize optimal behavior. First, $U(a)$ denotes the value of unemployment to an individual of age a. Second, $V(z, x, a)$ denotes the value of a match with productivity x between a firm with productivity z and an individual of age a, with the convention that $V(z, x_u, a)$ represents the expected value when match productivity is unknown. Third, $J(z)$ denotes the expected value of recruiting to a firm with productivity z. Appendix C specifies separately the value to an employed individual of age a of being employed in a firm with productivity z with match productivity x when paid wage w, $W^w(z, x, a, w)$, and the value to a firm of the same match, $W^f(z, x, a, w)$, to show that $V(z, x, a) = W^w(z, x, a, w) + W^f(z, x, a, w)$, i.e., the value of the match does not depend on how it is split. As this is a well-

[23] I numerically find that the model may have several stationary equilibria, where typically one is stable and the other unstable (in the sense that a small deviation from it will lead to either the firm productivity distribution exploding or the stable equilibrium). In these cases, I focus my analysis on the stable equilibrium. Appendix D discusses this in greater detail, as well as potential additional assumptions that could guarantee uniqueness.

known property of this class of offer matching models, I refer a further discussion to the appendix.[24] Consequently, all decisions made by the match are bilaterally optimal and to solve for the equilibrium allocation it suffices to work with the value of the match and of unemployment. Denote also by E the expected value of entry to entrepreneurship.

In order to characterize the value functions, the following four objects are necessary: First, $h(z)$ denotes the pdf of recruiting firms. Second, $f(z)$ denotes the *vacancy-weighted* pdf of recruiting firms. Third, $u(a)$ denotes the mass of unemployed workers of age a. Fourth, $g(z,x,a)$ denotes the pdf of employed workers. For all densities, upper case letters denote the corresponding cumulative density functions (cdf).

Unemployment. The value of unemployment solves,

$$\rho U(a) = b + \underbrace{\lambda\beta \int_0^\infty \max\left\{V\left(z, x_u, a\right) - U(a), 0\right\} dF\left(z\right)}_{\text{job offer}} + \underbrace{\kappa(a)\left[U(a+1) - U(a)\right]}_{\text{aging}} + \underbrace{\gamma(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c, 0\right\} d\Omega(c)}_{\text{entrepreneurship opportunity}} \tag{2}$$

An unemployed individual enjoys flow value b and meets vacancies at rate λ. If she accepts the job, she starts in a match with unknown quality and gets a slice β of the surplus. She ages at rate $\kappa(a)$, with the convention that $U\left(A+1\right) \equiv U(1)$ (since an individual is perfectly altruistic and her offspring enters as unemployed). Finally, at rate $\gamma(a)$ she draws a cost of starting a business. If she pays the cost, she gets the expected value of a new business and returns to unemployment.

An unemployed individual enters employment if she meets a firm, $z > \underline{z}^u(x_u, a)$, where the threshold $\underline{z}^u(x_u, a)$ is defined by,

$$U(a) = V\left(\underline{z}^u(x_u, a), x_u, a\right) \tag{3}$$

An unemployed individual attempts entrepreneurship if she draws a sufficiently low cost, $c < \bar{c}^u$, where the threshold $\bar{c}^u$ is defined by,

$$E = \bar{c}^u \tag{4}$$

The latter does not depend on age since an innovating individual instantaneously returns to unemployment.

[24] See for instance Cahuc et al. (2006), Jarosch (2015) and Borovickova (2016).

Match. The match solves an optimal stopping time problem to determine at what point $\underline{z}^u(x,a)$ to break up the match for unemployment. The value of a match with unknown productivity satisfies for $z > \underline{z}^u(x_u, a)$,

$$\rho V(z, x_u, a) = e^z - \underbrace{\mu \frac{\partial V(z, x_u, a)}{\partial z}}_{\text{drift in } z} + \underbrace{\frac{\sigma^2}{2} \frac{\partial^2 V(z, x_u, a)}{\partial z^2}}_{\text{shocks to } z} + \underbrace{\kappa(a)\left[\max\{V(z, x_u, a+1), U(a+1)\} - V(z, x_u, a)\right]}_{\text{individual ages}} + \tag{5}$$
$$+ \underbrace{\lambda\beta \int_0^\infty \max\{V(z', x_u, a) - V(z, x_u, a), 0\}\, dF(z')}_{\text{new job offer}} + \underbrace{\psi \sum_{i\in\{b,g\}} \pi(x_i) \max\{V(z, x_i, a), U(a)\} - V(z, x_u, a)}_{\text{match productivity is revealed}} +$$
$$+ \underbrace{\gamma(a) \int_{\underline{c}}^{\bar{c}} \max\{E - c - V(z, x_u, a) + U(a), 0\}\, d\Omega(c)}_{\text{entrepreneurship opportunity}}$$

I discuss each term of (5) in sequence. A match with unknown productivity in expectation produces e^z. On the BGP, firm productivity drifts down at rate μ and is subject to shocks with standard deviation σ. At rate $\kappa(a)$ the individual ages, with the convention that $V(z, x, A+1) \equiv U(1), \forall z, x$. At rate λ the individual gets a new job offer. If she switches employer, she gets the full value of her current match, plus a slice β of the surplus. The payoff to the firm in this case is zero, since it would have to pay the flow cost of creating a new vacancy and there is no capacity constraint in production.[25] At rate ψ, the match learns its productivity, which with probability $\pi(x_i)$ is productivity i, and optimally decides whether to quit. Finally, at rate $\gamma(a)$, the individual draws a cost of entry to entrepreneurship and enters if the cost is sufficiently low. A similar recursion characterizes the value of a match with known match productivity and can be found in Appendix C.

The recursions for the match define two reservation policies in addition to the exit boundary. First, an employed individual switches employer if she meets a new firm $z' > \underline{z}^e(z, x, a)$, where,

$$V(\underline{z}^e(z, x, a), x_u, a) = V(z, x, a) \tag{6}$$

In the case when an individual is in an unknown quality match, this reduces to simply $\underline{z}^e(z, x_u, a) = z$. V is intuitively increasing in z and x. Consequently, $\partial \underline{z}^e(z, x, a)/\partial z > 0$ and $x' > x \implies$

[25] There is no term for a "loss" to the firm of the worker moving on to a new job. The reason is that the worker obtains the full value of the current match from the new employer.

$\underline{z}^e(z, x', a) > \underline{z}^e(z, x, a)$—the higher a person is on the job ladder and the better suited she is for her match, the better the outside offer must be in order for her to accept it. Second, she enters entrepreneurship if she draws $c < \bar{c}^e(z, x, a)$, defined by,

$$E - \bar{c}^e(z, x, a) + U(a) = V(z, x, a) \tag{7}$$

It follows that $\partial \bar{c}^e(z, x, a)/\partial z < 0$ and $x' > x \implies \bar{c}^e(z, x', a) < \bar{c}^e(z, x, a)$. The higher up on the job ladder an individual is and the better she knows that her match is, the higher is her opportunity cost. Hence, the lower is the maximum cost she is willing to pay to enter entrepreneurship. Since a match optimally terminates at $\underline{z}^u(x, a)$, for $z < \underline{z}^u(x, a)$, $V(z, x, a) = U(a)$.

Firm. The firm solves an optimal stopping time problem of choosing at what point $\underline{z}$ to exit the recruiting market to avoid paying the fixed cost r, as well as how many vacancies to post.[26] That is, the firm solves for $z > \underline{z}$,

$$\begin{aligned} \rho J(z) = \max_{v \geq 0} \Bigg\{ & v(1-\beta)q \Bigg[\sum_a \Bigg(\underbrace{u(a) \max\{V(z, x_u, a) - U(a), 0\}}_{\text{value from meeting unemployed}} \Bigg) + \\ & \underbrace{+ (1-u) \int \max\{V(z, x_u, a) - V(z', x, a), 0\}\, dG(z', x, a)}_{\text{value from meeting employed}} \Bigg] - c_v \frac{v^{1+\eta}}{1+\eta} \Bigg\} - \underbrace{r}_{\text{fixed cost}} - \underbrace{\mu J'(z)}_{\text{drift in } z} + \underbrace{\frac{\sigma^2}{2} J''(z)}_{\text{shocks to } z} \end{aligned} \tag{8}$$

where $u(a)$ is the mass of unemployed of age a and $u = \sum_a u(a)$ is the aggregate unemployment rate. I discuss each term in (8) in sequence. At rate q, the vacancy contacts an individual, who with probability $u(a)$ is unemployed of age a. With probability $1 - u$ the individual is employed and randomly drawn from the distribution of employed individuals. The individual only accepts the new job if it is better than her previous job. In both cases, the firm gets a slice $1 - \beta$ of the differential value. For $z \leq \underline{z}$, $J(z) = 0$.

The optimal vacancy posting rule, $v(z)$, hence solves,

$$v(z)^\eta = \frac{(1-\beta)q}{c_v} \left[\sum_a u(a) \max\{V(z, x_u, a) - U(a), 0\} + (1-u) \int \max\{V(z, x_u, a) - V(z', x, a), 0\}\, dG(z', x, a) \right] \tag{9}$$

[26]Notice that when a firm exits the recruitment market, it does not automatically lead to the termination of previously created matches. Hence size is not a state for J.

In the calibrated model, as well as in the data, a large share of a firm's hires comes directly from other employers. Consequently, the distribution of employed workers, G, figures prominently in the firm's vacancy posting decision. In particular, if the distribution of employment moves up the job ladder—the labor market becomes less mismatched—that will tend to discourage vacancy creation by increasing the mass of individuals that will reject the job and improving the bargaining position of those that accept it.

Entrepreneurship. An individual who enters entrepreneurship draws an initial firm productivity z from cdf $\Phi(\cdot)$. She then gives the mutual fund a take-it-or-leave-it offer to purchase the business idea, whose value equals $J(z)$. Hence the expected value of entry equals,

$$E = \int_0^\infty J(z)d\Phi(z) \tag{10}$$

4.2 Laws of motion

Firms drift downward at rate μ and receive shocks at rate σ. Those that cross the exit threshold exit the recruiting market, while new recruiting firms enter with a productivity drawn from the innovation distribution ϕ.[27] That is, h solves the Kolmogorov forward equation (KFE),

$$0 = \mu h'(z) + \frac{\sigma^2}{2}h''(z) + e\zeta \exp(-\zeta z), \qquad z > 0 \tag{11}$$

subject to,

$$h(0) = 0, \qquad \int_0^\infty h(z)dz = 1, \qquad e = \frac{\sigma^2}{2}h'(0) \tag{12}$$

where e is the aggregate entry rate. The density at the boundary is zero since firms exit when they hit it, while by the nature of h being a density it must integrate to one. Finally, the mass of exiting firms equals $\sigma^2 h'(0)/2$, which in the stationary equilibrium has to equal the entry rate. This can be seen by integrating (11) from 0 to ∞, which gives $0 = -\mu h(0) - \sigma^2/2h'(0) + e$, and imposing $h(0) = 0$. The equation (11) subject to (12) is a second-order ordinary differential equation with solution,

$$h(z) = \frac{e}{\mu - \frac{\sigma^2}{2}\zeta}\left[\exp(-\zeta z) - \exp\left(-\frac{2\mu}{\sigma^2}z\right)\right] \tag{13}$$

[27]Note that if a random variable is Pareto with shape ζ and scale one, its log is exponentially distributed with rate ζ.

where the growth rate of the economy is a function of the aggregate entry rate of entrepreneurs,

$$\mu = \frac{e}{\zeta} \tag{14}$$

The solution can be verified by substituting (13)–(14) into (11) subject to (12).

The vacancy-weighted distribution of firms, $f(z)$, equals the density of recruiting firms at z times the amount of vacancies they post,

$$f(z) = \frac{v(z)h(z)}{\bar{v}}, \qquad \bar{v} = \int_0^\infty v(\tilde{z})\, dh(\tilde{z}) \tag{15}$$

where $v(z)$ is the solution to (9).

On the BGP, $g(z,x,a)$ satisfies the KFE

$$\begin{aligned} 0 =& \mu \frac{\partial g(z,x,a)}{\partial z} + \frac{\sigma^2}{2}\frac{\partial^2 g(z,x,a)}{\partial z^2} + \underbrace{\lambda \frac{u(a)}{1-u} f(z)\mathbb{1}\{x = x_u\}\mathbb{1}\{z > \underline{z}^u(x_u,a)\}}_{\text{inflow from unemployment}} + \underbrace{\kappa(a-1)\mathbb{1}\{z > \underline{z}^u(x_u,a)\}\, g(z,x,a-1)}_{\text{inflow from aging}} - \\ &- \underbrace{\kappa(a)g(z,x,a)}_{\text{outflow from aging}} + \underbrace{\lambda f(z)\mathbb{1}\{x = x_u\}\int \mathbb{1}\{z > \underline{z}^e(z',x',a)\}\, G(dz',dx',a)}_{\text{inflow from lower rungs in job ladder}} - \underbrace{\lambda\left[1 - F\left(\underline{z}^e(z,x,a)\right)\right] g(z,x,a)}_{\text{outflow to higher rungs in job ladder}} + \\ &+ \underbrace{\psi\mathbb{1}\{z > \underline{z}^u(x,a)\}\,\pi(x)g(z,x_u,a)}_{\text{inflow from learning}} - \underbrace{\psi\mathbb{1}\{x = x_u\}\, g(z,x,a)}_{\text{outflow from learning}} - \underbrace{\gamma(a)g(z,x,a)\Omega\left(\bar{c}^e(z,x,a)\right)}_{\text{outflow to entrepreneurship}} \end{aligned} \tag{16}$$

with the convention that $\pi(x_u) = 0$ and $g(z,x,0) \equiv 0, \forall z,x$, subject to the boundary condition that workers exit at the boundary so that the density is zero and the pdf integrates to one. I discuss the terms on the right-hand side of (16) in order. The distribution is subject to the drift $-\mu$ and shocks σ. At rate $\lambda f(z)$, an unemployed individual receives an offer from a firm with productivity z. If she accepts it, she starts out with unknown match productivity. There is a mass $u(a)$ of unemployed individuals of age a, which has to be adjusted for the fact that only $1-u$ individuals are employed. There is an inflow of aging individuals at intensity $\kappa(a-1)$ (to the extent that they remain in the market, $z > \underline{z}^u(x,a)$). At rate $\kappa(a)$, individuals flow out due to aging. At rate $\lambda f(z)$, employed individuals not currently working at z receive a job offer from a z firm. The offer is accepted if it is sufficiently better than their previous match, and the new match starts with unknown productivity. Individuals receive new offers at rate λ and they move out up the ladder if it is sufficiently good. For match productivities different than x_u, there is an inflow of individuals who learn their productivity and do not abandon the match. For match productivities with x_u, there is an outflow due to learning at rate ψ. Finally, individuals receive the opportunity to enter entrepreneurship at rate $\gamma(a)$. This is accepted if the cost is sufficiently low, leading to an outflow of individuals.

The mass of unemployed of each age group, $u(a)$, satisfies,

$$
\begin{aligned}
0 = &-\underbrace{\lambda\left[1 - F\left(\underline{z}^u(x_u, a)\right)\right] u(a)}_{\text{outflow to employment}} + \underbrace{(1-u(a))\sum_x \frac{\sigma^2}{2}\frac{\partial g(\underline{z}^u(x,a), x, a)}{\partial z}}_{\text{individuals drifting below the threshold}} + \underbrace{(1-u(a))\psi\pi(x_b)G\left(\underline{z}^u(x_b,a), x_u, a\right)}_{\text{individuals jumping below the threshold due to learning}} + \\
&+ \underbrace{\mathbb{1}\left\{a=1\right\}\kappa(A)}_{\text{newborn}} - \underbrace{\kappa(a)u(a)}_{\text{outflow from aging}} \underbrace{+\kappa(a-1)\left[u(a-1) + (1-u)\sum_x G\left(\underline{z}^u(x,a), x, a-1\right)\right]}_{\text{inflow from aging}} + \\
&+ \underbrace{(1-u(a))\gamma(a)\int \Omega\left(\bar{c}^e(z,x,a)\right) G(dz, dx, a)}_{\text{entry to entrepreneurship}}
\end{aligned}
\tag{17}
$$

with the convention that $u(0) = 0$. At offer arrival rate λ, unemployed individuals meet with hiring firms and enter employment if the firm is sufficiently productive. Employed individuals drift below the separation threshold at rate $\partial g\left(\underline{z}^u(x,a), x, a\right)/\partial z$. Individuals in unknown quality matches learn that their match is low quality at learning rate $\psi\pi(x_b)$, and they separate if their firm productivity is sufficiently low.[28] $\kappa(A)$ of newborn individuals start as unemployed. $\kappa(a)$ individuals age. There is an inflow due to aging of unemployed individuals and employed individuals who endogenously terminate their match as they age. Finally, at rate $\gamma(a)$, employed individuals receive the chance to enter entrepreneurship, which they accept if the associated cost is sufficiently low. They subsequently flow into the pool of unemployed.

It is not possible to derive a closed-form solution to (16)–(17). However, the quantitative analysis will confirm the natural intuition that a more negative drift, $-\mu$, results in more density in g on lower productivity firms. That is, higher growth results in more labor market mismatch.

Definition 1 (Stationary equilibrium)**.** *A BGP equilibrium consists of value functions $\{V, J, E, U\}$; optimal entry and mobility policies of unemployed and matches, $\{\bar{c}^u, \underline{z}^u(x,a), \underline{z}^e(z,x,a), \bar{c}^e(z,x,a)\}$; optimal exit and vacancy policies of firms, $\{\underline{z}, v(z)\}$; numbers $\{\lambda, q, \bar{v}, r, e, \mu\}$; masses of unemployed $u(a)$; and distributions $\{h(z), f(z), g(z,x,a)\}$; such that*

1. *U solves (2), V and $\underline{z}^u(x,a)$ solve the stopping time problem of the match (5), and the policy functions*

[28] To simplify the notation, I take as given that V is increasing in x so that if a match is viable with unknown quality, it is preserved when the match learns that it is good. This will be true in the quantitative analysis.

of the unemployed and the match are given by (3)–(4) *and* (6)–(7)*;*

2. *J and $\underline{z}$ solve the stopping time problem of the firm* (8) *and $\underline{z} = 0$, E is given by* (10)*, and the vacancy policy is given by* (9)*;*

3. *The aggregate entry rate e is consistent with individual behavior and the growth rate is given by* (14)*;*

4. *Aggregate vacancies $\bar{v}$ are consistent with firm behavior and the finding rates are given by* (1)*;*

5. *$h(z)$ is given by* (13)*, $f(z)$ by* (15)*, and $u(a)$ and $g(z, x, a)$ solve* (16)–(17)*.*

4.3 Intuition

Before bringing the model to the data, I briefly discuss the effect of aging in the model. To that end, denote by $\hat{G}(z, x|a)$ the age-conditional cdf of employment and by $m(a)$ the share of the labor force of age a. The aggregate JJ hazard can be written as

$$JJ = \lambda \int \left[1 - F\left(\underline{z}^e(z, x, a)\right)\right] dG(z, x, a) = \sum_a m(a) \frac{1 - \frac{u(a)}{m(a)}}{1 - u} \times \lambda \times \int \left[1 - F\left(\underline{z}^e(z, x, a)\right)\right] d\hat{G}(z, x|a) \tag{18}$$

At offer arrival rate λ, employed individuals receive outside offers sampled from the endogenous, vacancy-weighted distribution of firms F. They accept them if they are sufficiently better than their current jobs. This highlights four channels through which the aggregate JJ hazard may be affected by aging. First, a shift in the age distribution, $m(a)$, will affect the aggregate JJ hazard since older individuals typically are better matched and hence have a lower probability of making a JJ move. Second, λ may change as firms respond to the changed economic environment by adjusting vacancy creation. Third, F may change as firms change their vacancy posting decisions, which may or may not be associated with a change in λ.[29] Fourth, aging may give rise to changes in age-conditional labor market mismatch, $\hat{G}(z, x|a)$.

The aggregate entrepreneurship entry rate equals

$$\begin{aligned} e &= \frac{1}{M} \left\{ (1 - u) \int \Omega\left[\bar{c}^e(z, x, a)\right] \gamma(a) dG(z, x, a) + \Omega\left(\bar{c}^u\right) \sum_a u(a)\gamma(a) \right\} \\ &= \sum_a m(a) \frac{\gamma(a)}{M} \left\{ \left(1 - \frac{u(a)}{m(a)}\right) \int \Omega\left[\bar{c}^e(z, x, a)\right] d\hat{G}(z, x|a) + \frac{u(a)}{m(a)} \Omega\left(\bar{c}^u\right) \right\} \end{aligned} \tag{19}$$

[29] Aging may also affect what jobs individuals accept, $\underline{z}^e(z, x, a)$. The quantitative model finds that this effect is very small.

A mass $m(a)$ of age a individuals receive entrepreneurship opportunities at rate $\gamma(a)$ drawn from Ω. Of these, a fraction $1 - u(a)/m(a)$ are employed and enter if the cost is below $\bar{c}^e(z, x, a)$. A fraction $u(a)/m(a)$ are unemployed and enter if the cost is below $\bar{c}^u$. This is all divided by the total mass of recruiting firms, M. This highlights three channels through which the aggregate entry rate may be affected by aging. First, a shift in the age distribution, $m(a)$, will affect entry since age groups in general differ in their propensity to enter. Second, a change in the age composition may affect the optimal entry policy, $\bar{c}^e(z, x, a)$, as if for instance an older pool of potential hires discourages entry by driving up the effective cost of recruiting. Finally, through equilibrium effects aging may affect age conditional labor market mismatch, $\hat{G}(z, x|a)$, and unemployment, $u(a)/m(a)$.

Hence, the following takes place in response to aging. It reduces the aggregate JJ and entry hazards by tilting the workforce composition towards older, less mobile parts of the population, i.e., it changes $m(a)$. Moreover, the less mobile recruitment pool dissuades firms from posting vacancies and entrepreneurs from entering by driving up the effective cost of hiring—a change in $\bar{c}^e(z, x, a)$. When the entry rate falls, by (14) the process of creative destruction slows and μ falls. Incumbent firms do not fall behind the market as fast as before, which from (16)–(17) implies that individuals on average are employed higher up the job ladder also conditional on age. The shift in the age conditional distribution of employment, $\hat{G}(z, x|a)$, up the ladder further reduces the JJ and entry hazards by (18)–(19). The next two sections quantify the importance of these equilibrium mechanisms, highlighting what moments of the data inform their strength.[30]

5 Firm and Worker Life Cycle Dynamics

A life cycle of both firms and workers play a prominent role in the theory. This section brings the model to the data to show that it generates as a non-targeted equilibrium outcome life cycle firm and worker dynamics that closely match the corresponding empirical moments, providing confidence in the theory.

5.1 Strategy

Due to better data availability at the end of my sample period, I calibrate the model to match key moments in 2012–2014. In this sense, I run the experiment in the next section "backwards."

[30] Appendix C illustrates this intuition in a highly stylized version of the model.

Although it simplified the notation to specify the model in continuous time, several of the moments I compute later take complicated forms, such as annual reallocation rates at the firm level and higher-order moments of annual income innovations. This opts me to solve a discretized version of the model to compute these by simulation rather than derive PDEs that characterize them. Appendix D contains a detailed description of the algorithm I use to solve and simulate the model.

The model is solved at a monthly frequency. I first determine a set of standard parameters based on common values in the literature, summarized in Table 1. The discount rate is set to the monthly equivalent of a four percent annual real interest rate. Matching efficiency is not separately identified from the cost of vacancy creation, and hence I normalize χ.[31] I set the elasticity of the matching function with respect to vacancies to $\theta = 0.7$, which is a commonly estimated value when one allows for search on the job (Petrongolo and Pissarides, 2001). Finally, I set workers' bargaining power to $\beta = 0.3$, which is the average value across education groups estimated by Bagger et al. (2014). My results are not sensitive to other reasonable values for β or θ.[32]

TABLE 1. PRE-SET PARAMETER VALUES

	Description	Target	Value
ρ	Discount rate	Annual interest rate of 4%	0.0034
χ	Matching efficiency	Normalization	0.1
α	Elasticity of matching function	Petrongolo and Pissarides (2001)	0.7
β	Bargaining power	Bagger et al. (2014)	0.3

I approximate the life cycle with three age groups and set the monthly transition rate $\kappa(a)$ such that individuals expect to be young for 15 years (age 20–34), middle age for 10 years (35–44) and older for 15 years (45–59). The three age groups are set to roughly correspond to phases of life cycle dynamics documented in Appendix B.

The remaining 12 parameters are calibrated internally to match the 12 moments listed in Table 2. I discuss heuristically why these moments are particularly informative about some parameters, but the calibration is joint and hence all moments in general inform all parameters. All statements below should be interpreted as "holding everything else constant, if X is larger..."

As discussed in Section 2, the available evidence suggests that the recent decline in the UE

[31] In the discrete time approximation, the worker finding rate of a vacancy cannot be larger than one. Normalizing χ to a sufficiently low value ensures this.

[32] Tenure wage profiles and wage gains from JJ mobility are partly informative about β. I show in Appendix D that the model under this parameter value closely matches empirical estimates of these moments.

hazard may be an artifact of the Great Recession rather than a secular phenomenon. In light of this, I calibrate c_v to target the average UE hazard in 2005–2007, which is 17 percent. The results are not sensitive to the exact value for c_v. The aggregate EU hazard informs the probability that the match is low productive, $\pi(x_b)$. If this is small, the EU hazard is low. The aggregate JJ hazard informs the productivity of high productive matches, x_g. If this is high, the JJ hazard is low since individuals who have learned that they are high productive would have to sacrifice more to switch employers. The rate of learning, ψ, is informed by the tenure profile of the JJ hazard.[33] If ψ is high, uncertainty about match productivity is rapidly resolved and the JJ hazard falls quickly with tenure. Few good estimates are available on the flow value of leisure. Hence, I set it such that a young individual with unknown match productivity is indifferent between working for the least productive hiring firm and unemployment.

The average firm entry rate informs the average of the arrival rate of entrepreneurship opportunities across age groups. Differences in the arrival rate of opportunities by age are calibrated to match entrepreneurship entry rates by age. As noted in the previous section, this is the only parameter that I allow to vary directly with age. Little evidence is available on the dispersion in the cost of entering entrepreneurship, and hence I assume that it is uniformly distributed between $-C$ and C. The dispersion in entry costs, C, is informed by the fall in entry with tenure. If the cost distribution is dispersed, large changes in the value of entry are required to achieve a given change in the number of individuals who enter entrepreneurship. With tenure, the opportunity cost of entry increases; hence, the extent to which entry declines with tenure informs C. Finally, recall from (14) that the growth rate is directly linked to the entry rate and the shape of the innovation distribution, ζ. I calibrate ζ to Luttmer (2007)'s estimate that 65 percent of growth is due to selection of firms applied to the 1.7 percent growth rate in 2012–2016.[34] I have considered alternative reasonable values for ζ with similar results.

I set the mass of marketing specialists, M, to match average firm size, and the elasticity of the vacancy cost function, η, to match the share of employment of entrant firms in size bins 1–249, 250–499, 500–999, and 1000+ employees. When η is high, the cost of creating jobs increases rapidly in vacancy creation. Hence, it is expensive to rapidly increase employment, and entrant firms will

[33] I construct tenure profiles of mobility using pooled SIPP data from 1996 onwards for which tenure is available, and adjust the level to match that in the late period.

[34] As discussed further below, I additionally introduce a death shock to firms, which implies a slightly more complex mapping between the entry rate and the growth rate than (14). Nevertheless, the same intuition holds.

be smaller. I introduce a small probability of firm death that is independent of firm productivity for the following reason. The unweighted entry rate is implicitly determined by the entrepreneurship and firm growth parameters discussed above, which pins down the unweighted exit rate (since unweighted entry equals unweighted exit in equilibrium).[35] Without a small death shock destroying some large firms, the weighted exit rate is too low because not enough workers work at firms close to the separation threshold.[36] Finally, σ is set to match the the share of employment of all firms in size bins 1–249, 250–499, 500–999, and 1000+ employees. A more volatile productivity process implies greater dispersion in productivity in the stationary economy, which translates into greater dispersion in firm size in equilibrium.

TABLE 2. CALIBRATED PARAMETER VALUES

	Description	Target	Value
Panel A: Labor market mobility			
c_v	Cost of vacancy creation	Average UE	$4.5 * 10^{-4}$
$\pi(x_b)$	P(match is low productive)	Average EU	0.5
x_g	Productivity of high prod. match	Average JJ	1.3
ψ	Rate of learning	Timing of decline in JJ with tenure	0.043
b	Flow value of unemployment	Indifference at margin	1.09
Panel B: Entrepreneurship			
$\nu(a)$	Entrepreneurship opportunity	Entry rate by age	$[4.2; 4.5; 2.1] * 10^{-3}$
C	Dispersion in entry cost	Decline in entry with tenure	72
ζ	Innovation distribution	Growth due to selection (Luttmer, 2007)	20
Panel C: Incumbent firms			
M	Marketing specialists	Average firm size	0.13
η	Curvature of vacancy creation	Size distribution of entrants	2
d	Exit shock for firms	Average exit rate	$3.8 * 10^{-4}$
σ	Shocks to productivity	Size distribution	$7 * 10^{-3}$

35 The model somewhat overstates the level of the unweighted entry rate, which is 13.8 percent in the model versus 8.0 percent in the data in the late period. To the extent that some small (typically one worker) firms enter as unincorporated businesses, they would not be captured by the data, which only cover incorporated businesses.

36 At the calibrated values, about three quarters of the employment-weighted exit rate is due to firms falling below the endogenous separation threshold, and the remaining quarter due to the exogenous death shock (practically all of the unweighted exit rate is due to endogenous exit). Apart from allowing me to match the exit rate, introducing this exogenous death shock has no meaningful impact on results.

5.2 Properties of the calibrated economy

I comment briefly on some of the calibrated parameters and the model fit. The probability that a match is good is calibrated to 0.5, in which case it is 30 percent more productive than expected productivity. The calibrated learning parameter implies that half of matches will have learned their productivity in two years, i.e., learning is quite slow. This is implied by the slow decline in the JJ hazard with tenure. The flow value of unemployment that makes individuals indifferent between entering at the lowest productivity firm and remaining unemployed is high. This results from individuals not giving up any option value to enter employment, but gaining the option value to learn that their match is high productive. The estimated standard deviation of shocks to firm productivity implies a steady-state standard deviation of marginal productivity of 0.14.[37]

Since the model fits the targeted aggregate firm and worker reallocation rates very well, to avoid repetition I refer to Tables 3–4 in the next section for the numbers.[38] The top two panels of Figure 1 plot the JJ hazard and entrepreneurship entry hazard by tenure in the model and data. Appendix D also shows that the model matches well the tenure profile of the EU hazard. The bottom two panels plot the distribution of employment by firm size of all firms and entrant firms. The model fit is overall good.

Figure 2 compares the implied life cycle profiles of the EU and JJ hazards in the model with their empirical counterparts. As individuals age, they climb the job ladder and learn about match quality. It takes time, however, to find a productive employer, and even then it is not guaranteed that the individual will be a good fit with the firm. Furthermore, employers are subject to continuous shocks to their productivity, necessitating constant worker reallocation. It adds up to produce a rather time-consuming process. Recall that the calibration only targets the aggregate EU and JJ hazards.[39] Matching the life cycle profiles of these hazards so well supports the proposed job ladder and learning mechanisms as important factors behind life cycle worker dynamics.[40]

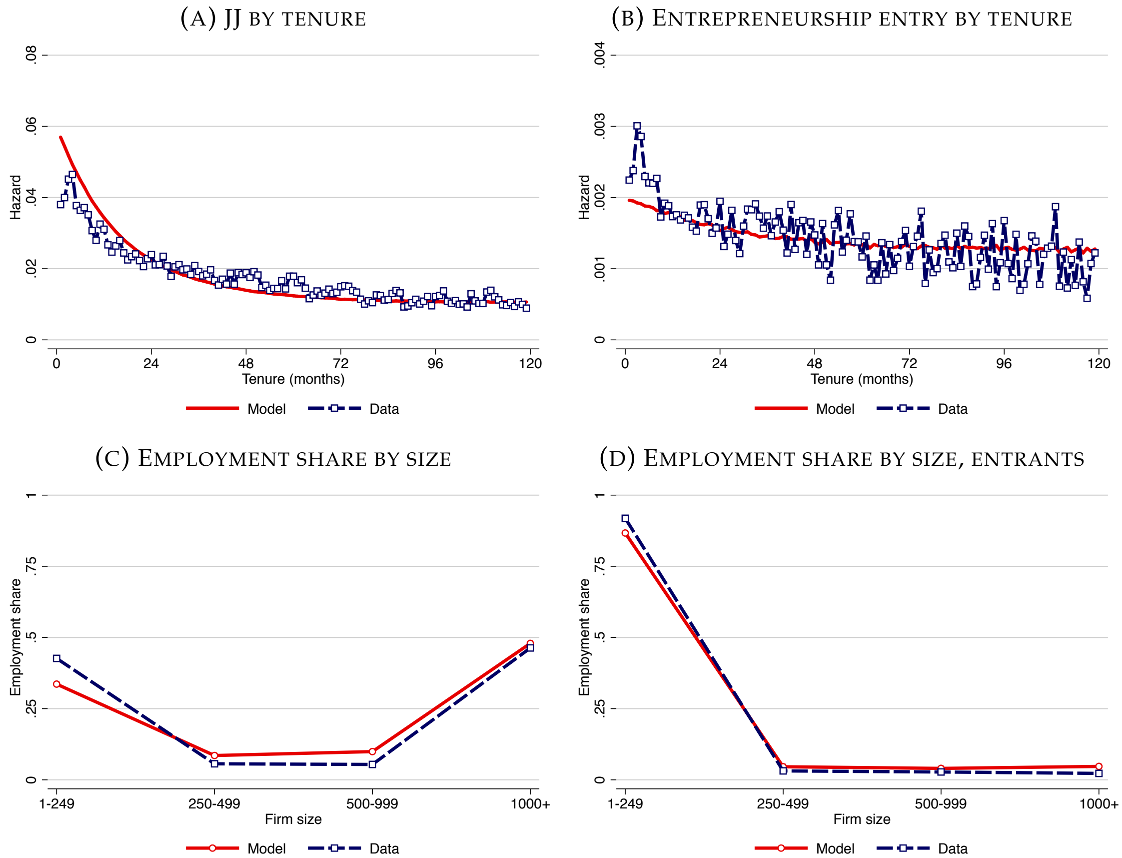
[37] Decker et al. (2017a) report a standard deviation of within-detailed industry dispersion in log TFP of just over 0.4 in 2011 (see their Figure 1). Empirical measures of value added and TFP are known to be plagued by substantial measurement error, which may account for the discrepancy.

[38] Additionally, the model predicts an average firm size of 31.5 versus 33.2 in the data, and a life cycle profile of entrepreneurship entry that matches the data perfectly.

[39] Note the if the JJ hazard falls by X percent between zero and long tenures, the rate of learning, ψ, determines how early on in a match the X percent fall takes place. It does not govern the magnitude of the fall, X.

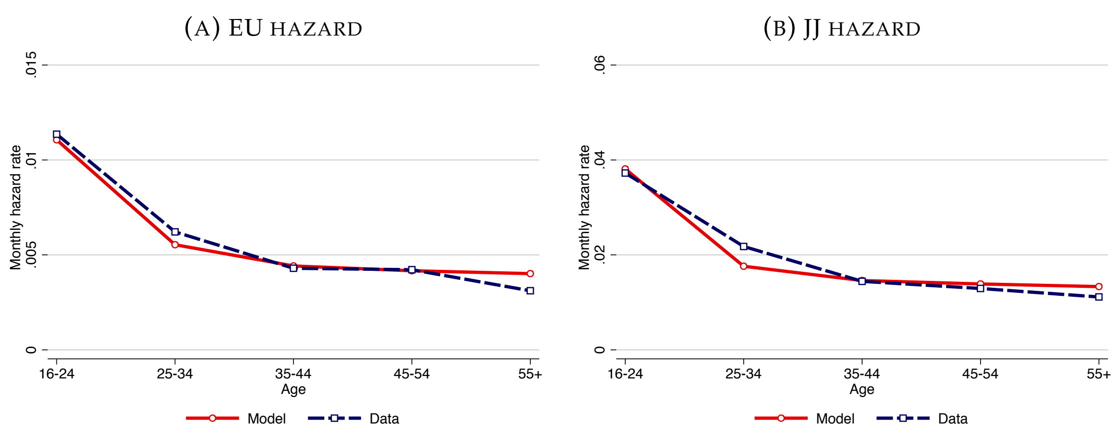
[40] Appendix D shows that the model predicts a flat UE hazard over the life cycle, while the hazard falls modestly in the data. To the extent that individuals become less likely to make an UE move as they age, the fact that the model does not match this will likely lead to an underestimate of the impact of aging. Appendix D also shows that the model matches well empirical wage-tenure profiles, gains from JJ mobility, the variance of annual income, and the second, third and fourth moments of annual income innovations.

FIGURE 1. MODEL FIT: JJ TENURE PROFILE, ENTREPRENEURSHIP ENTRY TENURE PROFILE, EMPLOYMENT SHARE BY FIRM SIZE, AND EMPLOYMENT SHARE BY FIRM SIZE OF ENTRANTS



Note: SIPP 1996–2013 adjusted to the level in 2013 and BDS in 2014 (HP-filtered annual data with smoothing parameter 6.25). JJ: share of employed in t who are with a different employer in $t+1$; entrepreneurship entry: share of employed in month t who are self-employed in $t+1$.

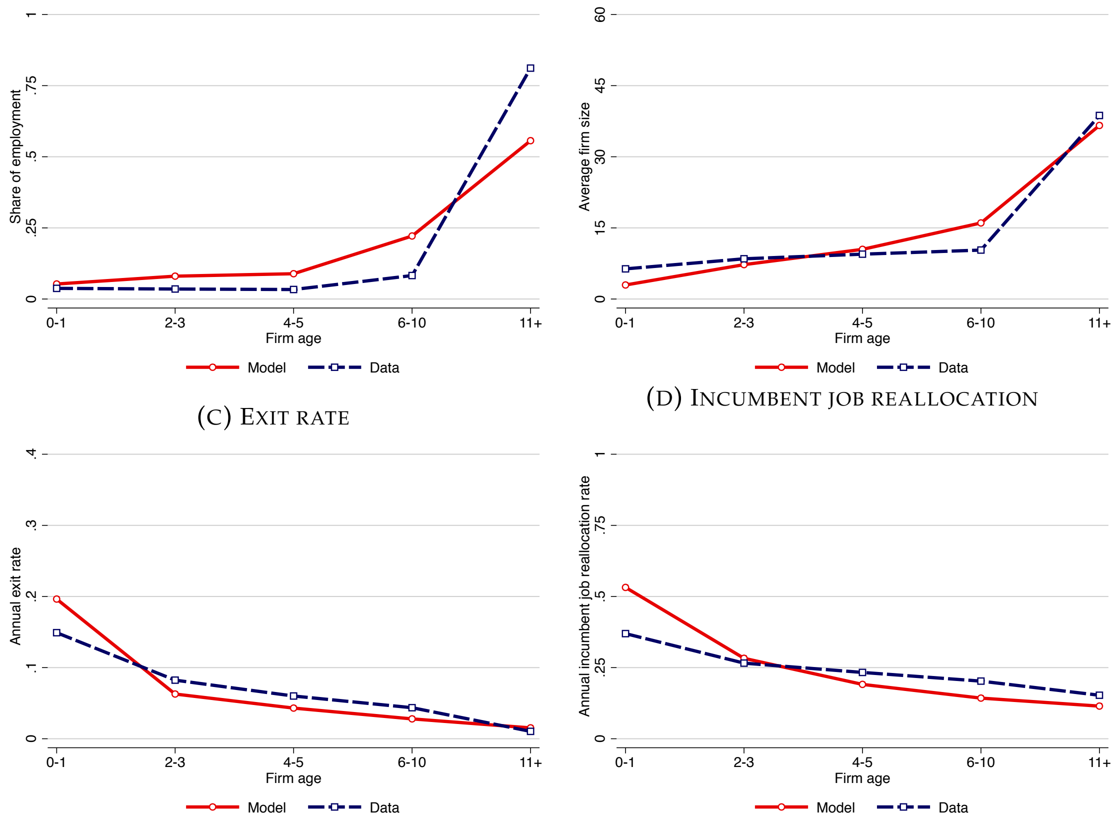
FIGURE 2. VALIDATION: LIFE CYCLE WORKER DYNAMICS



Note: SIPP 2011–2013 (HP-filtered annual data with smoothing parameter 6.25). JJ: share of employed in t who are with a different employer in $t+1$; EU: share of employed in month t who are unemployed in $t+1$.

FIGURE 3. VALIDATION: LIFE CYCLE FIRM DYNAMICS

(A) EMPLOYMENT SHARE | (B) AVERAGE FIRM SIZE | (C) EXIT RATE | (D) INCUMBENT JOB REALLOCATION



Note: BDS in 2014 after HP-filtering the data. Exit rate: sum of employment of firms whose employment in the subsequent year is zero; Incumbent job reallocation: sum of job creation of expanding non-entrant establishments and job destruction of contracting non-exiting establishments; Firm age: years lapsed since first year with positive employment. All within firm age groups and divided by total employment in that age group. Exit and firm size are adjusted to match the empirical mean.

FIGURE 4. VALIDATION: LINKING FIRM AND WORKER DYNAMICS

(A) DATA | (B) MODEL

Note: Reproduced from Davis et al. (2010) based on JOLTS micro data for 2001–2006. Data are monthly and model-simulated data quarterly. Hiring rate: sum of hires between time t and $t+1$; Separation rate: sum of separations between time t and $t+1$; Employment growth: change in employment between t and $t+1$; all divided by to total employment at time t. Weighted by employment and multiplied by 100.

The top left panel of Figure 3 illustrates that in both the model and the data most individuals work for old firms, with the model understating somewhat the share of employment at very old firms. The next three panels show that the model matches well average firm size by age, the exit rate by age, and job reallocation for incumbents by age.[41] I note that any error in the measurement of firm age will tend to bias the decline with age in the empirical profiles towards zero.

Recall that the calibration targets average firm size, employment shares by firm size, employment shares by firm size of entrants, the aggregate entry and exit rate, and an estimate of the contribution of firm selection to economic growth. Hence, it is not by construction that the model replicates so well life cycle firm dynamics. In particular, the drift and standard deviation of the productivity process are calibrated to match very different moments, yet the model matches well job reallocation for incumbents by firm age. It suggests that the proposed combination of a geometric Brownian motion for productivity, firm selection through creative destruction, and labor markets frictions captures key stylized facts on life cycle firm dynamics.

Figure 4 illustrates that the model captures the hockey stick-like link between the hiring and separation rate at the establishment level and establishment-level employment growth as documented by Davis et al. (2010).[42] I note in particular that in both the model and the data the hiring rate rises more than one-for-one with employment growth. An expanding establishment hires workers whose productivity is unknown, resulting in an elevated churn rate.[43]

6 Quantifying the Effects of Aging

Having confirmed that the model replicates key features of firm and worker dynamics in the data, I proceed to analyze the impact of aging through the lens of the model. To that end, I

[41]Given that the model understates the share of employment at very old firms, these firms are the largest and have the lowest exit rates, and I additionally target average firm size and the average exit rate, I will overstate (understate) somewhat the age-conditional firm size (exit rate) by construction. Figure 3 normalizes the average firm size and the exit rate to the average in the data to highlight the pattern with age. I prefer to get the overall average firm size and exit rate right rather than the level of the age-conditional firm size and exit rates, but I have verified that this preference has no meaningful impact on results. Appendix D shows the unadjusted graphs.

[42]I use quarterly model-generated data, while the data are monthly. Using a monthly frequency in the model deemphasizes this pattern since I do not allow an employment spell to start and end in the same month in the model. Supposedly this restriction is not present in the real world. Aggregating to the quarterly level allows for short, within-period transitions.

[43]Appendix D shows that the model fits well a range of additional moments. This includes a fat-tailed distribution of firm quarterly employment changes; hires and separations from and to employment and unemployment, respectively, with firm age; a modestly increasing share of hires that are poached from other firms by firm age; a declining net poaching rate by firm age; an increasing average age of workers by firm age; the decline in the exit rate by firm size; as well as the magnitude of the firm age and firm size pay gradients and between-firm dispersion in pay.

change the age composition of the economy and evaluate its implications for business dynamism, labor market fluidity and economic growth. In order to achieve a decrease in the share of older individuals in line with the data, I change the rate at which older individuals exit the market, $\kappa(3)$, from 0.0043 in the late period to 0.0087 in the early period. Changing $\kappa(3)$ while keeping $\kappa(1)$ and $\kappa(2)$ constant leads me to understate the increase in the share of young and overstate the increase in the share of middle aged somewhat. As young individuals are more mobile than middle aged people and have about the same entrepreneurship entry rates, this will result in an underestimate of the effect of aging.[44]

The change in $\kappa(3)$ has two effects: First, it increases the share of young people, and second it shortens the time individuals expect to remain in the market. In the data, on the other hand, the retirement age has not increased over this period, which suggests that individuals did not expect to spend less time in the market in the 1980s. To achieve the first effect while purging the results from the second, I use the original $\kappa(3)$ when solving the value functions, and the new $\kappa(3)$ when computing individual transitions (i.e., in the laws of motion (16)–(17)). That is, individuals continue to behave as though they expect to spend as much time in each age group as before. Although I believe that this is the most appropriate way to map the non-stationary real world into the model environment, results are effectively the same if I do not offset the direct effect.[45]

6.1 The decline in business dynamism

Table 3 summarizes the predicted effect of aging on firm reallocation rates. According to the model, aging explains 56 percent of the empirical change in firm turnover and 39 percent of the fall in job reallocation over this period. In line with the data, both entry and exit fall substantially.[46] Furthermore, a substantial share of the decline in job reallocation is driven by falling job reallocation for incumbents. These predictions are in line with the first set of empirical facts in Section 2.

Figure 5 illustrates that aging in the model explains key changes in the life cycle dynamics of firms over this period. The left panel shows that employment has shifted substantially towards

[44] I have also considered a specification where I also adjust $\kappa(2)$ to fully match the change in the age distribution, with modestly more pronounced results. Table 14 in Appendix E summarizes the age distribution in the model and the data in the early and late period.

[45] This is not surprising given the dynastic preference structure, which assumes that older individuals are perfectly altruistic with respect to their offspring. In ongoing work, I am pursuing an extension to study the transition path.

[46] Given that I assume that the exogenous death shock remains fixed, it is not surprising that as a fraction the model explains less of the change in the exit rate than in the entry rate.

older firms as the turnover rate of firms has slowed. Since older firms are less dynamic, from an accounting perspective, the shift towards older firms accounts for some of the decline in firm dynamics. I show in Appendix E that aging in the model replicates the empirical fact that the shift towards older firms accounts for all (or more) of the decline in exit and a substantial share of the decline in job reallocation for incumbents. While in both the model and the data the weighted exit rate did not fall conditional on firm age, the unweighted exit rate has declined within firm age groups. The middle panel shows that aging in the model reproduces the empirical pattern that the exit rate has declined by more in relative terms for old firms. The right panel shows that firm size has fallen the most for young firms over this period, which aging in the model largely replicates. The harder recruiting environment hampers firm growth, resulting in smaller firms conditional on age. In contrast, average firm size has increased modestly in both the model and the data due to the rapid shift towards older firms, which are on average larger.

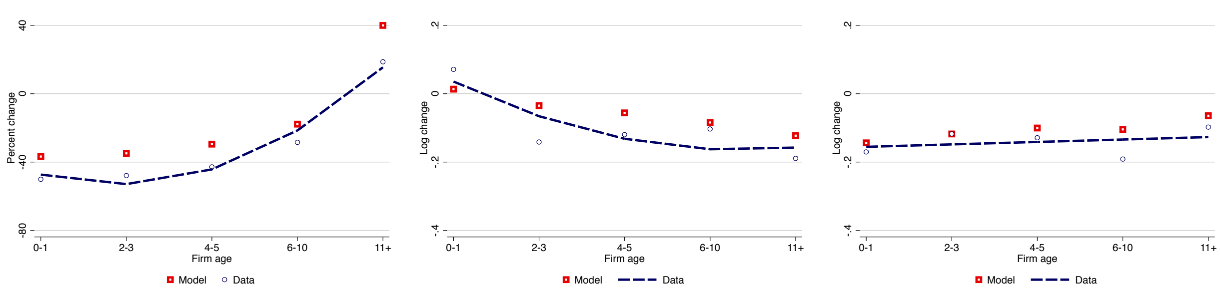
TABLE 3. IMPACT OF AGING ON BUSINESS DYNAMICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early		Late		Change		
	Data	Model	Data	Model	Data	Model	Share
Entry	0.037	0.033	0.020	0.021	-0.018	-0.012	65.4
Exit	0.028	0.021	0.019	0.018	-0.009	-0.003	35.6
Turnover	0.065	0.054	0.039	0.039	-0.026	-0.015	55.8
Incumbent	0.213	0.176	0.166	0.152	-0.046	-0.024	52.7
Job	0.345	0.231	0.246	0.191	-0.100	-0.039	39.2

Note: Annual firm reallocation rates from the BDS in 1986 and 2014 after HP-filtering with smoothing parameter 6.25.

FIGURE 5. CHANGE IN FIRM LIFE CYCLE DYNAMICS

(A) EMPLOYMENT SHARE (B) EXIT RATE (C) AVERAGE FIRM SIZE



Note: Data from the BDS in 1988 and 2014 after HP-filtering the annual data with smoothing parameter 6.25. Employment share: sum of employment by firms in that age group divided by total employment; Exit rate: number of exiting firms divided by total number of firms in that age group; Average firm size: sum of employment at firms in that age group divided by number of firms in that age group. Difference between late and early period.

Job reallocation may be viewed as the second moment of employment changes at the firm level. Based on this, Decker et al. (2017a) document four empirical patterns over this period. First, the fall in job reallocation is not due to a more benign economic environment facing firms. Second, older firms adjust employment less in response to productivity shocks. Third, employment has shifted towards older firms, accounting for some of the decline in the response of firm employment to firm productivity shocks. Fourth, the response has fallen within firm age groups. The model replicates this pattern. First, the variance of underlying productivity shocks is held constant. Second, firms' employment response to changes in idiosyncratic productivity is (partly) tied to the number of ranks a firm moves in the ladder in response to a shock. If a firm changes many ranks, this has a large effect on the number of workers it loses and gains for a given number of vacancies posted, which is amplified through its effect on optimal vacancy creation.[47] The (log) productivity distance between ranks of firms is larger further up the ladder, and hence a given magnitude productivity shock does not move a firm as many ranks at the top of the ladder, leading to a smaller employment response.[48] Older, surviving firms are on average further up the ladder, resulting in them endogenously having a lower pass-through. Third, as noted above, aging in the model leads to a substantial shift of employment towards older firms. Fourth, employment has also shifted up the ladder within firm age groups, leading to a decline in the pass-through conditional on firm age. Table 15 in Appendix E provides more details.

6.2 The fall in labor market fluidity

Table 4 summarizes the predicted effect of aging on worker flows. Aging explains 36 percent of the change in the EU hazard and 48 percent of the change in the JJ hazard in the data.[49] The decline in worker reallocation is only partly due to the decline in job reallocation, with also a significant fall in churn.[50] In contrast, the UE hazard only declines slightly. This is in line with the set of facts on worker flows presented in Section 2.

[47] Additionally, vacancies respond proportionally less at the top of the ladder due to the strict convexity of the cost function.

[48] Given that higher-ranked firms are typically larger, an implication of this is that the variance of growth rates is higher for small firms. This is a robust feature of the data (Sutton, 1997; Caves, 1998). Despite all firms being subject to the same proportional productivity process, the model generates this as an endogenous equilibrium outcome arising from the presence of labor market frictions.

[49] In light of the fact that the SIPP experienced a break in the JJ series in 1996, the exact empirical decline in the JJ hazard is somewhat uncertain. See Appendix A for a further discussion and robustness.

[50] The model accounts for 38 percent of the decline in quarterly churn in the QWI from 1993–2014.

TABLE 4. IMPACT OF AGING ON LABOR MARKET FLUIDITY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early		Late		Change		
	Data	Model	Data	Model	Data	Model	Share
EU	0.009	0.006	0.005	0.005	-0.003	-0.001	35.7
JJ	0.023	0.020	0.018	0.017	-0.005	-0.002	47.6
UE	0.175	0.169	0.170	0.168	-0.005	-0.001	24.8

Note: Monthly worker reallocation rates from SIPP in 1986 and 2012–2013 (2005–2007 for UE), first converted to annual averages and then HP-filtered with smoothing parameter 6.25.

The model reconciles the difference in behavior between the JJ and UE hazards through the following mechanism.[51] Conditional on productivity, firms post fewer vacancies in the older economy as they face a better matched labor market. On the other hand, the slower turnover rate of firms implies that the distribution of firms has shifted to the right, and more productive firms post more vacancies. The net effect is only a small decline in the job finding rate (Appendix E illustrates this). In contrast, the less dynamic economy implies that employment has shifted up the ranks of firms and a higher share of matches have learned that they are high productive. As individuals higher up the ladder and who know that they are in a high-productive match are less likely to accept a job offer, this has reduced the JJ hazard over and above the modest decline in the offer arrival rate.

Figure 6 plots the relative decline in the EU, JJ and UE hazards by age in the model in red squares. The model suggests a relatively larger effect on mobility rates late in careers when individuals have moved up the ladder. In the next section, I use cross-state variation to find a pattern in the data that corresponds to what the model suggests. This is plotted in dashed blue.[52]

To relate my structural analysis to a literature that typically finds a limited role of aging in the slowdown in worker reallocation, I employ a commonly used shift-share analysis on model-generated and actual data. That is, I compute age conditional mobility rates in a late period, β_a^{late},

[51] Additionally, the JJ hazard falls with age while the UE hazard does not; hence, a composition effect accounts for some of the difference.

[52] In contrast, the raw CPS and SIPP data provide different results with respect to this. The SIPP suggests that in relative terms the EU hazard has fallen uniformly across age groups while the JJ hazard has declined the most among young individuals; the CPS indicates the largest relative declines in the EU hazard among young individuals and a roughly uniform relative decline in the JJ hazard with age. One interpretation of this is that other forces at work over this period have particularly reduced mobility of younger individuals. It is an interesting task for future research to understand these other forces better.

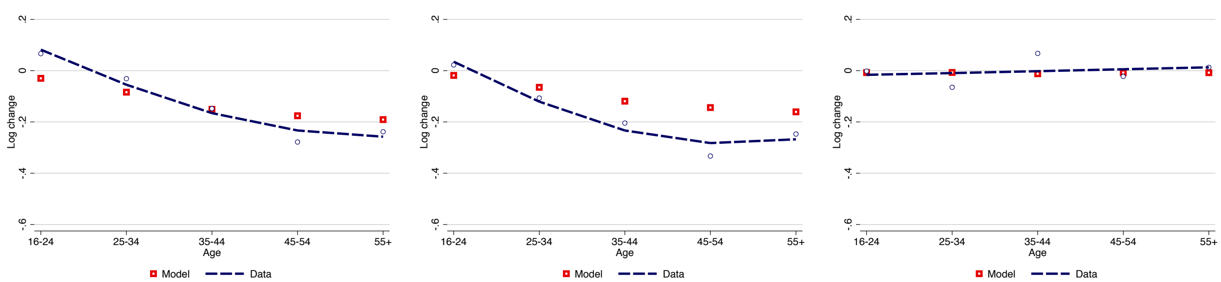
and change the age composition assuming that age-conditional mobility rates remain constant,

$$\widehat{\text{Effect of aging}} = \sum_a \beta_a^{\text{late}} \left[\text{share of labor force}_a^{\text{early}} - \text{share of labor force}_a^{\text{late}}\right]$$

Table 17 in Appendix E shows that the predicted effect of aging based on this methodology in the model accounts for 60 percent of the predicted effect in the data using the same methodology.[53] More importantly, this approach leads to a substantially understated role of aging in the decline in worker dynamics. It suggests that aging only accounts for 35–50 percent of the overall decline in the EU and JJ hazards in the model, respectively. Effectively, this reduced form approach treats the age-conditional mobility rates, β_a, as structural parameters which remain fixed in response to changes in the age composition, which the model suggests is not a valid assumption.

FIGURE 6. CHANGE IN WORKER LIFE CYCLE DYNAMICS

(A) EU (B) JJ (C) UE



Note: Log difference in reallocation rate from early to late period. Data: estimated based on cross-state panel regressions within age groups controlling for state fixed effects, year effects and growth in state real GDP per individual. CPS 1978–2014 (starting in 1994 for JJ).

6.3 A level and a growth effect

The model implies that aging has reduced annual economic growth by 0.27 percentage points. Over this period, trend growth in real GDP per labor force participant has fallen from 2.6 percent in 1984–1988 to 1.7 percent in 2012–2016. At the same time, fewer individuals are unemployed in the late period. The unemployment rate has declined from 6.2 percent to 5.2 percent in the model versus 6.9 percent to 5.8 percent in the data.[54] Table 5 summarizes these predictions.

[53] Two reasons are behind why the model understates the predicted effect of composition in the data. First, it is not possible to perfectly match the change in the age composition by changing only one parameter, $\kappa(3)$. As noted above, I chose a conservative approach which understates the direct effect of aging. Second, the model understates somewhat the declines in these hazards over the life cycle.

[54] Targeting hazard rates leads me to understate the unemployment rate. Instead recalibrating the model to match the unemployment rate, I find essentially identical results.

TABLE 5. IMPACT OF AGING ON AGGREGATE ECONOMIC OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)
	Early		Late		Change	
	Data	Model	Data	Model	Data	Model
Growth	2.6	1.42	1.7	1.15	-0.9	-0.27
Unemployment rate	0.069	0.062	0.058	0.052	-0.011	-0.010

Note: Annual growth in real GDP per labor force participant 16 years of age and older in 1984–1988 and 2012–2016, as well as the unemployment rate in 1986 and 2015. Annual data from the BEA and BLS HP-filtered with smoothing parameter 6.25.

In contrast to the negative growth effect, the model implies that aging has had a positive level effect on output, as summarized in Table 6. Output has increased by 1.4 log points due to a composition effect (older individuals are always better matched). It has risen further by 4.4 log points due to the shift of employment up the job ladder within age groups, while the shift in match productivity has had only a modest effect. Net output has increased by less than the sum of these effects because more resources are spent on vacancy creation—even though firms create fewer vacancies conditional on productivity, the underlying distribution of firms has shifted to higher productivity firms which have a higher marginal cost of vacancy creation since they create more vacancies.[55] Discounted net output has fallen by four log points due to the lower growth rate.

TABLE 6. IMPACT OF AGING ON LEVEL OF OUTPUT, MODEL

(1)	(2)	(3)	(4)	(5)
Age composition	Firm productivity	Match productivity	Net output	Discounted net output
0.014	0.044	0.004	0.055	-0.040

Note: Log change in output going from the young to the old economy due to composition effect, shift in firm productivity, change in share of high productive matches, change in net output after subtracting cost of vacancies and entry, and discounted change in net output.

6.4 Quantifying the channels

To highlight the channels through which aging reduces the JJ and entry hazard, I decompose the changes based on equations (18)–(19). I start from the model calibrated to the old economy and gradually turn on each channel.[56] The direct effect of the shift, $m(a)$, generates a seven percent increase in JJ mobility. The effect of changes in firm vacancy creation, $\lambda(1 - F(\underline{z}^e(z, x, a)))$, accounts

[55] Resources spent on entry has fallen, but not by enough to offset the change in the resource cost of vacancies.
[56] Although this decomposition is not invariant to the order in which effects are included, changing the order has no meaningful effect on the conclusions.

for a 17 percent *decrease* in the JJ hazard. For the reasons mentioned above, the job finding rate, λ, is only modestly higher in the younger economy. The vacancy-weighted distribution of firms, $F(z)$, however, shifts to firms further down the ladder, with a lower probability that the individual will accept the offer holding everything else constant.[57] The shift in F is the result of less productive firms disproportionately benefitting from the easier recruiting environment in the younger economy as well as a shift in the underlying distribution of firms. Finally, the faster turnover rate of firms leads to greater labor market mismatch conditional on age, i.e., it shifts $\hat{G}(z, x|a)$ towards lower productivity firms and a higher share of matches with unknown match productivity. This reduces the opportunity cost of a JJ move and accounts for a 23 percent increase in JJ mobility, of which 20 percentage points are due to the shift in the firm productivity dimension.

The shift in the age composition, $m(a)$, generates a 10 percent increase in entry. The shift in the entrepreneurship entry decision rules, $\bar{c}^e(z, x, a)$ ($\bar{c}^u$), in response to the easier recruiting environment accounts for a one percent increase in the entry rate. Although a higher turnover rate of firms increases the value of entry by shifting employment down the firm ladder, it also reduces the value since a potential entrant expects to be replaced faster.[58] Finally, the shift in $\hat{G}(z, x|a)$ accounts for a further 10 percent increase in the entry rate, of which less than one percentage point is due to the shift in match productivity. Table 7 summarizes these results.

TABLE 7. DECOMPOSING THE CHANGE IN THE JJ AND ENTRY HAZARD, MODEL

	(1)	(2)	(3)	(4)
	Entry hazard		JJ hazard	
	% change	% of total	% change	% of total
Direct effect	10.5	47.5	7.0	53.6
Policies: $\bar{c}^e(z, x, a)/\lambda\,[1 - F(\underline{z}^e(z, x, a))]$	1.2	5.4	-17.3	-133
Mismatch: $\hat{G}(z, x\|a)$	10.4	47.2	23.3	179
Total effect	22.2	100	13.1	100

Note: Unweighted entry and JJ mobility in the young economy as a percent of that in the old economy. Channels are turned on sequentially starting from the top.

I note that the above decomposition is for the unweighted entry rate. The weighted entry rate is an additional 30 percentage points higher in the young economy as entrant firms post more vacancies and hire more individuals per posted vacancy in response to the easier recruiting

[57]The shift in the acceptance policy, $\underline{z}^e(z, x, a)$, has a negligible effect.

[58]Furthermore, the market effect on entry is linked to the incremental value created by an entrant over the least productive incumbent, and both incumbents and entrants are affected by the shift in labor market mismatch.

environment. A similar pattern holds in the data over this period: the weighted entry rate is an additional 30 percentage points higher than the unweighted entry rate in 1986 compared to 2014.

The decomposition highlights some of the key parameters governing the strength of the equilibrium effects of aging and what moments of the data inform them. The tenure profile of JJ mobility informs to what extent individuals become harder to recruit as they climb the ladder and learn their match productivity. If this is flat, JJ mobility will not increase much in response to the worse-matched labor market, and hence, the recruiting environment for firms will not be significantly affected. Similarly, the tenure profile of entry informs the elasticity of entry with respect to changes in the value of entry. If this profile is flat, entry will not respond much to the potential entrant being further up the ladder, having learned her match productivity, or facing a different hiring market. Figure 1 in the previous section showed that the model matches these empirical counterparts well. This discussion highlights that the large estimated equilibrium effects of aging are not hardwired into the model but implied by key moments of the data.[59]

6.5 Summary

The model implies that aging has reduced business dynamism, labor market fluidity and economic growth in line with key secular trends over this period. On the firm side, turnover has declined both because entry and exit have fallen, job reallocation has declined also because incumbent firms have become less dynamic, and the latter is due to firms' weaker employment response to shocks. On the worker side, the EU and JJ hazards have declined substantially, but not the UE hazard, and a shift-share analysis indicates a large role for equilibrium effects. Finally, the model implies that aging has reduced annual economic growth by 0.27 percentage points.[60] The next section provides additional empirical support for the predictions of the model using variation across US states in the incidence of aging over this period.

[59] Appendix E verifies that the model matches well the tenure distribution over this period using CPS tenure supplements. Of course, the fact that the model matches changes in the stock—tenure—may not be surprising given that it matches well changes in flows over this period. Nevertheless, it serves as a potentially useful robustness exercise in light of the above discussion.

[60] Appendix E shows that aging in the model also captures well changes in a range of additional dimensions over this period, including a modest shift of employment towards larger firms, a decline in the variance of annual income innovations, and an increasing negative skewness of annual income shocks.

7 Additional Empirical Support of the Hypothesis

To provide additional empirical support to the hypothesis that aging has had important effects on dynamism, I exploit variation in the incidence of aging across US states from 1978–2014 in a panel regression framework. The implicit assumption underlying this approach is that the effects of aging work at the level of the state, so that variation in the timing and magnitude of aging across states can be used to shed light on its effects on dynamism.

The demographic data come primarily from the Annual Social and Economic Supplements of the CPS (March CPS), which I complement with data on the lagged age composition from the US Census Bureau's Intercensal Censi projections.[61] Data on establishment and firm dynamics are from the BDS. I use merged CPS monthly files for worker mobility rates, since the SIPP is not large enough to compute mobility rates at the state-year-age group level. Finally, I construct state real GDP per worker using estimates of state private sector GDP from BEA, regional CPIs from the BLS, and private sector employment from the BDS. Appendix A contains further details on the construction of the data.

7.1 Methodology

I start by regressing various measures of establishment or firm dynamism, $y_{s,t}$, on the share of the labor force or population aged 19–64 that is aged 40–64 in state s in year t, a full set of state fixed effects, ξ_s, $T-1$ year effects, ξ_t, and time-varying controls, $\mathbf{X}_{s,t}$,

$$y_{s,t} = \text{older}_{s,t} + \xi_s + \xi_t + \mathbf{X}_{s,t}\beta + \varepsilon_{s,t} \tag{20}$$

I have considered specifications with reallocation rates and the share of older in both logs and levels. As aging predicts somewhat less of the declines based on the specification in logs, I use that as the benchmark to be conservative (results in levels are available in Appendix F). All state-years are equally weighted and standard errors are clustered by state and year.[62] Two-way clustering of standard errors in this way accounts for errors being correlated both within a state over time

[61] The correlation between the share of older individuals in the Intercensal Censi and the March CPS is not one. As using the Census estimates typically provides even more pronounced results, I use the CPS as a baseline to be conservative (this also allows me to separately look at the age composition of the labor force, which is not available from the Census).

[62] I have verified that my results hold when weighing states by population. I have also verified that my results are robust to excluding Alaska, which saw particularly rapid aging and declines in dynamism over this period.

as well as between states at a given point in time (Cameron et al., 2011; Thompson, 2011). Foote (2007) argues that accounting for this is important when using US state-level data.[63]

In a world where people move in and out of the labor force, it is not a priori clear whether the age composition of the labor force as opposed to the working age population provides the more relevant measure for understanding the effects of aging on the labor market. In light of this, I consider both specifications and find similar results.[64]

All my specifications control for growth in state real GDP per worker. I potentially control also for the share of females, the share of non-white, the share with a college degree (in the benchmark all in logs), the share of the labor force in nine aggregate sectors (again in the benchmark in logs), and a measure of the total state tax rate—accounting for income taxes, corporate taxes, sales taxes, et cetera—constructed by the Tax Foundation for each state for 1978–2012, and the state minimum wage.

To investigate the correlation between aging and worker mobility, I consider a slightly augmented version of the specification (20). Specifically, I let $y_{s,t}^{a}$ denote the EU, JJ and UE hazard of worker age group a in state s in year t, where a is one group of 19–24, 25–34, 35–44, 45–54 and 55–64. I use this as my left-hand side variable and include also a set of dummies for each of the age groups on the right-hand side. All state-year-age bins are equally weighted. Finally, I study the relationship between aging and economic growth by letting the annual growth rate in state real GDP per worker be the left-hand side variable in specification (20).

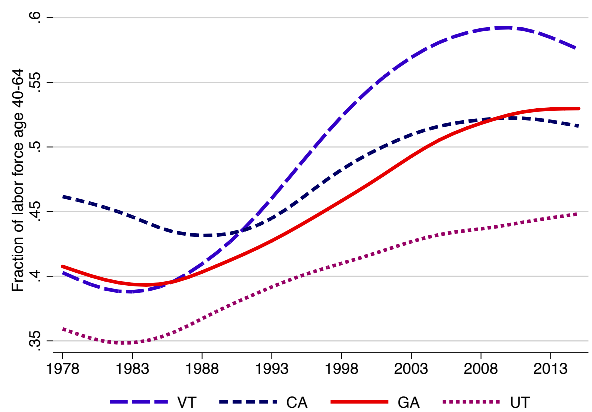
Identification. Identification of the specification (20) comes from differential changes in the age composition of a state over time across states. To illustrate that there are indeed important differences across states in both the timing and magnitude of aging, Figure 7 plots the share of the working age population that is older in four selected states (one in the Northeast, one in the South, one in the Mountain region, and one in the West). Although all states (in fact all 50 states) experienced increases in the share of people in this age group since the 1980s, both the magnitude and

[63] I have also experimented with adjusting standard errors based on methods developed by Driscoll and Kraay (1998) and Thompson (2011) to account for an even more complex error structure, but this does not meaningfully change my conclusions. These results are available on request. With respect to Foote (2007), I also note that my sample contains 10–18 more years of data than Shimer (2001), which alleviates small-T concerns.

[64] I have also considered a specification with the share in four age groups: 19–24, 25–34, 35–44 and 45–54. Although including the share of the labor force in several age groups potentially affords a more detailed understanding of the correlation between the age structure and labor market dynamism, having only one group helps interpretation and simplifies the IV-strategy by avoiding multiple endogenous regressors. This specification delivers similar results in terms of the overall predicted effect of aging over this period, and is available on request.

timing of these changes differ importantly across states. The empirical framework exploits this variation to study to what extent it correlates with within-state changes in dynamism.

FIGURE 7. SHARE OF WORKING AGE POPULATION THAT IS OLDER IN FOUR SELECTED STATES



Note: US Intercensal Population estimates 1978–2015. Share of population aged 19–64 that is 40–64.

Identification in the OLS framework relies on the assumption that aging is exogenous to dynamism. This would be violated if workers move across states in response to variation in dynamism. As noted by Shimer (2001), however, the worry is not as simple as for instance older people always moving to Florida, since that would be accounted for by the state effects. The concern is if one particular age group disproportionately moves in response to *temporary* variation in dynamism, such as if for instance a boom in firm entry in Florida induces disproportionately many young people to move into Florida in the years of the boom.[65] Notice also that the specification (20) includes controls for growth in state GDP per worker, so such temporary differential mobility trends by age would have to be in response to a component of dynamism that is orthogonal to GDP growth to potentially pose a problem.

To partly address such concerns, I instrument for the current age distribution using the 10-year lagged age distribution.[66] The exclusion restriction is that the 10-year lagged age composition only affects current dynamism through its effect on the current age distribution. I caution that although this specification may provide an improvement to the baseline OLS specification, concerns about

[65] When using the age composition of the labor force, a similar concern arises if, say, older people disproportionately drop out of the labor force in response to a decline in firm entry. The fact that results are similar using the age composition of the working age population suggests that this is not a first-order issue for the question at hand.

[66] Specifically, the share of the population of 6–55-year olds 10 years earlier that is 30 years or older. 10 years is chosen since annual Intercensal population estimates from the Census Bureau are only available starting in 1969.

reverse causality remain. That is, it may be that those aged 9–29 move differentially across state borders than those aged 30–54 in response to dynamism 10 year later. Once again, however, such mobility would have to be in response to a component of 10-years later dynamism that is orthogonal to growth in state real GDP per worker in order to be a problem.[67] Appendix F presents first-stage regressions, showing that the lagged age composition has a high explanatory power on the current age composition.

7.2 Results

Table 8 presents point estimates and their standard error on the share of older individuals based on the specification (20). Columns 1–2 show baseline results with the age composition of the labor force and columns 3–4 with the age composition of the working age population. Across all specifications, the estimated coefficient on the share of older individuals does not appear to be driven by the participation margin. Similar results hold adding covariate controls, sector controls, and the limited measures of policy, suggesting that the correlation between aging and dynamism does not arise through a change in sectoral policy, state taxation or the state minimum wage.[68] These results are available in Appendix F.

Panel A shows that across all specifications, a greater share of older individuals is negatively correlated with establishment turnover. Job reallocation is also lower, and by more than what can be explained by establishment turnover alone (indicating lower incumbent dynamics). A similar pattern holds for firm dynamics in Panel B, with even more pronounced results. The point estimates are larger in the IV specification. Taken at face value, this appears at odds with the hypothesis that part of the negative correlation between the share of older individuals and

[67]I have also considered a specification that instruments for the current share of older individuals in state s by the total number of people age 40–65 born in state s, regardless of where they currently reside. I construct this based on Decennial Censi 1970–2000 and annual American Community Survey data from 2001 onwards, interpolating linearly between Census years. Although even more pronounced results hold under this specification, there are concerns about a weak first-stage once one takes into account the fact that the i.i.d. assumption is likely violated. Hence, it is not clear how much to make out of these results. These results are available in Appendix F. In ongoing work, I am further exploring other instruments.

[68]A related hypothesis is that differences in the age composition is associated with differences in demand, as would be the case if younger people consumed very differently from older people. I note with respect to this that all my regressions control for growth in state real GDP per worker, which to some extent should capture such a demand-driven boom. I also note that non-durable consumption displays an almost symmetric inverse u-shape over the life-cycle with a peak at aged 45–50 such that it has not fallen back to the level at age 22 until age 70 (Fernández-Villaverde and Krueger, 2007). This speaks against this hypothesis, although more research is needed on this. If data had been available at the state-sector level, this hypothesis could have been further tested by restricting attention to sectors producing tradable goods. Unfortunately, such data are not made available by the BDS.

dynamism is driven by endogenous cross-state mobility.[69]

TABLE 8. ESTIMATED COEFFICIENT ON THE SHARE OF OLDER INDIVIDUALS

	(1)	(2)	(3)	(4)
	Labor force		Working age pop.	
	OLS	IV	OLS	IV
Panel A: Establishment dynamics				
Job reallocation	-0.448***	-0.527***	-0.518***	-0.539***
	(0.127)	(0.191)	(0.124)	(0.186)
Turnover	-0.630***	-0.961***	-0.774***	-0.984***
	(0.203)	(0.268)	(0.202)	(0.256)
Entry	-0.668***	-0.999***	-0.753***	-1.022***
	(0.189)	(0.247)	(0.188)	(0.245)
Exit	-0.600**	-0.940***	-0.809***	-0.962***
	(0.243)	(0.322)	(0.239)	(0.304)
Panel B: Firm dynamics				
Turnover	-0.764***	-1.266***	-0.923***	-1.296***
	(0.230)	(0.302)	(0.223)	(0.299)
Entry	-0.827***	-1.361***	-0.932***	-1.393***
	(0.199)	(0.278)	(0.195)	(0.291)
Exit	-0.712**	-1.203***	-0.921***	-1.231***
	(0.298)	(0.355)	(0.283)	(0.339)
Panel C: Worker dynamics				
EU hazard	-0.441***	-0.926**	-0.495***	-0.941**
	(0.146)	(0.375)	(0.160)	(0.406)
JJ hazard	-0.501**	-0.112	-0.642***	-0.127
	(0.226)	(0.728)	(0.215)	(0.824)
UE hazard	-0.091	-0.223	-0.024	-0.227
	(0.126)	(0.273)	(0.123)	(0.280)
Panel D: Growth				
GDP per worker growth	-0.066	-0.090**	-0.063	-0.092**
	(0.047)	(0.040)	(0.043)	(0.039)

*Note: BDS, BEA, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population aged 19–64 that is aged 40 and older based on model (20). Panel A–B control for state, year and annual growth in state real GDP per worker; Panel C controls for state, year, age and annual growth in state real GDP per worker; Panel D controls for state and year. All shares and reallocation rates are in logs. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Panel C shows that an older workforce is negatively correlated with the EU hazard, controlling for the individual's own age. The IV estimate is again larger than the OLS estimate. A larger share of older is also associated with a lower JJ hazard, but the IV estimate is smaller and not statistically significant. The JJ regressions are based on a substantially reduced sample since the measure is only available starting in 1994, which may account for the lack of statistical significance. There

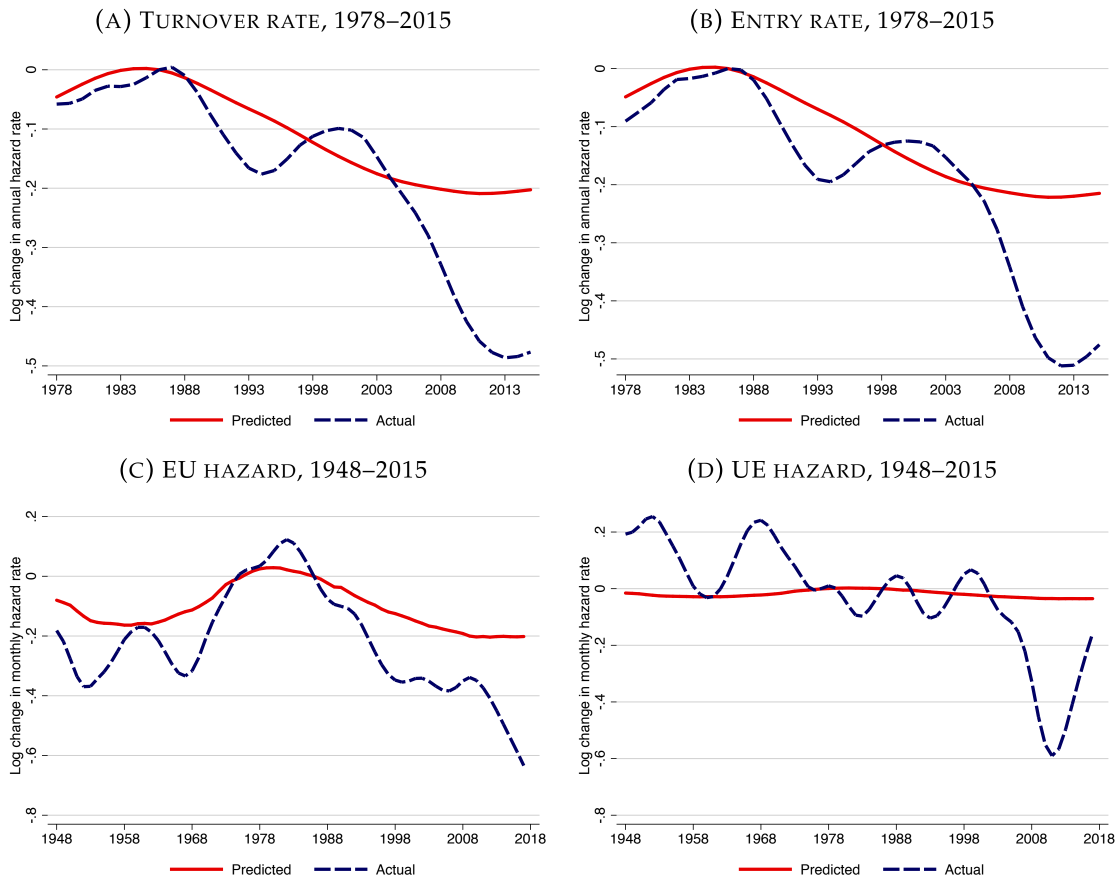
[69] I have also conducted tests developed by Davidson and MacKinnon (1993) to test for the exogeneity of the current age distribution. I cannot reject that it is exogenous to dynamism.

is no evidence of a correlation between aging and the UE hazard. Finally, Panel D shows that an older workforce is negatively correlated with economic growth, but only the IV estimates are statistically significant.

To illustrate the magnitude of the point estimates, I use the estimated coefficients from the panel regressions to predict dynamism at the national level over this period. I emphasize that this exercise is only meaningful under several strong assumptions. First, the estimates must obviously reflect a causal relationship. Although the IV specification gets somewhat closer to causality, there remains a concern that also the 10-year lagged age composition is endogenous to current dynamism (conditional on state fixed effects, year effects, and state GDP per worker growth). Second, it assumes that the cross-state estimates are informative about the time trend at the national level. To the extent that there are effects of aging that work at the national level but not the state level, these predictions may understate or overstate the true impact of aging on dynamism in the US over this period. It is difficult to address these concerns without more structure, which serves as a key motivation for interpreting the data through the lens of a structural model. Nevertheless, it remains of interest to compare the magnitude of the cross-state estimates to the changes in dynamism over this period.

Figure 8 plots the predicted impact of aging on establishment turnover, establishment entry, the EU hazard and the UE hazard at the national level based on the OLS panel estimates, normalized to zero in 1986 (the IV estimates provide an even more pronounced picture). I use data on EU mobility, UE mobility and the age composition of the labor force from the BLS to extend the series for the EU and UE hazard back to 1948. If the cross-state panel estimates reflect a causal relationship and they are informative about the effects of aging at the national level, they would imply that aging explains over 40 percent of the declines in establishment turnover, entry and the EU hazard, while accounting for little of the recent decline in the UE hazard. The direct effect of aging accounts for only a third of the predicted variation in the EU hazard. Appendix F summarizes these predictions, showing that even more pronounced conclusions hold using measures of firm dynamics or unweighted establishment or firm turnover rates, that aging also predicts 30–60 percent of the decline in the JJ hazard, and that similar results hold regardless of whether the labor force or working age population is used. Aging predicts a substantial, one percentage point decline in GDP per worker growth, but the error bound is wide.

FIGURE 8. PREDICTED IMPACT OF AGING ON SELECT MEASURES OF DYNAMISM



Note: BDS, BLS, CPS and Intercensal Censi 1948–2015. Predicted change in establishment turnover, establishment entry, the EU hazard and the UE hazard due to aging at the national level based estimates in column 1 in Table 8 in solid red, raw data in dashed blue.

7.3 Other important changes

Aging is only one of several important changes to the US labor force over the last decades. I briefly discuss four other prominent changes (see Appendix B for further details). First and second, the US labor force has become increasingly gender and racially diverse over this period. Including the share female and non-white in regression (20), however, neither coefficient is typically statistically significant. Furthermore, predicting the change in dynamism due to these factors, the predicted effect is small (typically a net increase). Hence, although the US labor force has become more diverse along these dimensions, the changes have been relatively small, statistically not associated with changes in dynamism and if anything predict a small increase in dynamism.

Third, the share of the labor force with a college degree or more has risen substantially over this period. Across most specifications, the share with a college degree is associated with higher dynamism such that the predicted effect of changes in education goes the "wrong" way.[70] Although I interpret these results very cautiously in light of the fact that educational choices are endogenous, at least as a first pass it does not appear as though changes in educational attainment explain the large decline in dynamism over this period.

Fourth and related to the changing age composition of the labor force, labor supply growth has slowed over this period. The decline was particularly pronounced in the late 1970s and early 1980s, as the baby boomers entered the labor market. As noted earlier, in recent, related work Karahan et al. (2016) argue that the decline in labor supply growth may explain up to a quarter of the fall in firm entry over this period. I verify their conclusion that labor supply growth is positively correlated with entry by including it in regression (20). This, however, has no significant effect on the estimated coefficient on the share of older individuals, which remains statistically significant and economically large.[71] Appendix F presents a full range of results controlling for labor supply growth. I conclude that although falling labor supply growth over this period is relevant for understanding the entry margin, changes in the age composition remain of first-order importance.

8 Conclusion

The US has aged substantially over the past 30 years, while business dynamism, labor market fluidity and economic growth have declined. This paper embeds endogenous growth through creative destruction in an equilibrium job ladder model, and finds that aging explains 40–50 percent of the declines in business dynamism and labor market fluidity, and a 0.27 percentage point decline in annual economic growth. Cross-state variation supports these predictions.

Several questions remain. Although important, aging typically accounts for half or less of the large declines in dynamism over this period. In light of this, an important outstanding question is what other factors contributed to the declines. Lower labor supply growth may have contributed to reduced firm entry (Karahan et al., 2016) while occupational licensing (Kleiner and Krueger, 2013), higher training requirements (Cairo, 2013) and more stringent employment protection (Autor et al., 2007) may be factors behind lower worker reallocation. More research is needed to better understand the large declines in dynamism in the US over this period.

[70] This should not be confused with the *direct* effect of education on worker reallocation, which is typically negative.

[71] The decline in labor supply growth also predicts *increases* in the exit rate, the EU hazard and the JJ hazard.

Anecdotal evidence suggests that population aging has contributed to a sclerotic labor market and poor economic growth in other countries, for example Japan. Yet a rigorous cross-country analysis is currently missing. Although such a study is complicated by the lack of long-time series of comparable data across countries, the increasing availability of administrative data may make it feasible. In light of rapidly aging populations in many developed countries, more research is needed to understand its effects on labor market performance.

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A Additional Details on Data

A.1 Sources

BDS. The BDS is based on micro data on firms and establishments collected in the Longitudinal Business Database by the Census Bureau. The data are publicly available at https://www.census.gov/ces/dataproducts/bds/. It provides aggregate measures on business dynamism at the establishment and firm level for the U.S. private-sector economy.[72] It excludes self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. Annual data are currently available at the state level for 1977–2015. It also provides more disaggregated data by sector, size and age of the firm (but not separately by state). The BDS measures employment as the number of full- and part-time employees on March 12 every year. This includes employees on paid sick leave, holidays, and vacations. The measure is at the establishment level, defined as a fixed physical location where economic activity occurs. The BDS also contains data aggregated up to the firm level, where a firm is defined as the highest level of operational control.

BEA. State private sector GDP is available from the Bureau of Economic Analysis (BEA), https://www.bea.gov/regional. I also use total real GDP and real GDP per hour available from the BEA.

BLS. The BLS publishes data on the total number of employed, unemployed and short-term unemployed workers back to 1948, as well as the number of employed and unemployed by age groups. Data on unemployment by duration is not available broken down by age. These data are available at https://www.bls.gov/cps/cpsatabs.htm. I use seasonally adjusted series.

The BLS also publishes regional CPIs which I use to construct real GDP per worker. These are available to download at https://www.bls.gov/regions/.

CPS. The CPS is conducted by the United States Census Bureau for the Bureau of Labor Statistics. The survey interviews about 60,000 households at a monthly frequency on a short rotating basis and is designed to be representative of the U.S. civilian non-institutionalized population. In March

[72] Alternative measures of firm dynamics are provided by the Business Employment Dynamics (BED) dataset starting in 1991. I use the BDS since it provides a preferable definition of a firm and a longer time series, but also the BED displays a sharp decline in firm dynamics over the period it covers.

every year the CPS fields the Annual Social and Economic supplement—commonly known as the March CPS—which collects demographic characteristics on household residents. The CPS micro data are available at the state level starting in 1977, with earlier surveys aggregating states into groups.[73] Since two of the explanatory variables of interest are annual growth rates of labor supply and state GDP per worker, I start my analysis in 1978.

I use two sources of data from the CPS. First, I obtain data on the characteristic of a state's labor force by year from the March CPS downloaded from https://cps.ipums.org/cps/. Specifically, I compute the fraction of the labor force or working age population that is female, non-white, college-educated (including more than college), and in five age bins (19–24, 25–34, 35–44, 45–54 and 55–64), as well as the growth in private sector employment, the labor force and working age population. An individual is in the labor force if she is employed or unemployed. I recode race to non-Hispanic white or not, and education to less than college or college or more. I also compute the share of employment in each of nine aggregate sectors in each state-year. All computations use the provided March CPS individual weights.

Second, in addition to the March CPS, I merge monthly basic CPS data to create a short panel. Specifically, I use the code kindly made available for public use by Robert Shimer,[74] combined with basic monthly files downloaded from http://www.nber.org/data/cps_basic.html. See Shimer (2012) for a further discussion of the issues involved in linking individuals across months in the basic CPS files. The short panel allows me to estimate flows from employment to unemployment (EU) and from unemployment to employment (UE) by state and year for 1978–2015. I also use the fact that since the introduction of dependent interviewing techniques with the 1994 redesign of the CPS, the survey asks whether an employed worker works for the same employer as last month. All computations use the provided basic monthly CPS weight. I use merged CPS monthly files for worker mobility rates, since the SIPP is not large enough to compute worker mobility rates at the state-year-age group level.[75]

Global Entrepreneurship Monitor (GEM). The GEM was designed with an explicit attempt to try to capture early entrepreneurial activity. I use this to construct life cycle profiles of entry into

[73] Specifically, the available March CPS micro data identifies states from 1962–1967, then aggregates states from 1968–1976, and then again identifies states from 1977 onwards.

[74] https://sites.google.com/site/robertshimer/research/flows

[75] A literature going back at least to Abowd and Zellner (1985) notes that the merged CPS data suffer from classification error as well as non-random missing values, which tend to inflate measured worker flows. In my calibration exercise, I hence prefer to rely on SIPP data.

entrepreneurship. See Liang et al. (2016) for further details.

Intercensal Censi. I complement the March CPS demographic data with data on the lagged age composition from U.S. Census Bureau's Intercensal Censi projections to construct the 10 year lagged age composition. The Intercensal Censi estimates are available from `https://seer.cancer.gov/popdata/download.html` at an annual frequency back to 1969.[76]

The Kauffman Firm Survey (KFS). I use the KFS from 2004–2010 to study post-entry performance of start-ups by age of the founder. This data source provides a panel of newly started businesses that are followed during the first years after inception.

The Panel Study of Entrepreneurial Dynamics (PSED). I use the PSED from 2005–2010 to study post-entry performance of start-ups by age of the founder. As the KFS, this data source provides a panel of start-ups that are followed during the first years after inception.

SIPP. The SIPP is conducted by the Census Bureau in several separate panels from 1984 to 2013. Each panel lasts 2.5–4 years and follows between 14,000–52,000 households, interviewing respondents once every four months (a so called *wave*). The explicit longitudinal design of the SIPP alleviates concerns in the merged CPS data of classification error (Nagypál, 2008).

The SIPP asks for a respondent's employment status in each month during the prior four months. It also collects details on up to two employment spells and two self-employment spells, including the start and possible end dates of the spells. I define a worker as employed in a month if she is working at least one week during the month, as unemployed if she is not working the entire month but looking for a job, and otherwise as not in the labor force. I note that these definitions will imply some time aggregation bias when computing worker flows. I also assign a main employer to an employed worker in a month as the spell the worker worked for most hours in the month.

A well-known issue with the SIPP is so called seam bias: an outsized share of transitions are reported between waves rather than within waves. To the extent that a transition is eventually reported, properly aggregating data should avoid the bias. To this end, I drop the last wave of

[76]To obtain the age composition in 1968, which is the earliest year I use, I linearly interpolate the 1960 Census and the 1969 Intercensal Censi estimates.

any individual and compute the mean of monthly worker flows at the panel-wave level. I assign the date of that panel-wave as the third month in that panel-wave, and subsequently aggregate the panel-wave data to the annual level. All measures are weighted by the provided person-level weights, adjusted such that each panel receives the same aggregate weight (this is only relevant for the pre-1996 panels since they overlap). Finally, there was a significant redesign of the SIPP in 1996, which caused a break in the series for JJ mobility (Mazumder, 2007; Nagypál, 2008). I discuss in further detail below how I potentially adjust for this.

State economic policy. I use a measure of total state taxation per capita by year from the Tax Foundation for 1977–2012,[77], and state minimum wages from the Washington Center for Equitable Growth for 1974–2016.[78] The state minimum wage is the maximum of the average state minimum wage in that year and the average federal minimum wage in that year. The tax rate as computed by the Tax Foundation is a measure of the total applicable tax rate for a state resident in that year, including sales taxes, corporate taxes, income taxes, local property taxes, etc.

QWI. The QWI provides aggregate data based on state unemployment insurance records provided to the Census Bureau as part of the Longitudinal Employer-Household Dynamics (LEHD) micro data collection. It excludes federal employees (but covers local and state employees in addition to private sector employment). The underlying micro data in the LEHD is at the job-worker-quarter level. The concept of an employer is that of an Employer Identification Number (EIN). Based on this, the QWI constructs aggregate statistics on employment, hires, separations, job creation and job destruction by state and quarter. It also provides data broken down by firm characteristics (geography, industry, age, size) and worker demographics information (sex, age, education, race, ethnicity). Data are available for an increasing number of states over time, with 32 states going back to 1998.

A.2 Variable definitions

Entrepreneurship entry. Following Liang et al. (2016), I define entry in the GEM as being actively involved in the management of a business that has paid owners' salaries and wages for at

[77] https://taxfoundation.org/state-and-local-tax-burdens-historic-data/ (downloaded on March 27, 2017).

[78] http://equitablegrowth.org/working-papers/historical-state-and-sub-state-minimum-wage-data/ (downloaded on June 15, 2017).

most 42 months and owning all or part of the enterprise. I alternatively consider several more stringent definitions of entry. In one, I additionally condition on entering because the individual saw a business opportunity in contrast to not having a better choice for work.[79] In another, I condition on either having hired at least one, five or 10 people at the time of the survey or expecting to hire one, five or 10 people over the next five years. The latter addresses facts uncovered by Hurst and Pugsley (2011) that a non-trivial share of entrants do not expect to grow, which may be different from the concept of entrepreneurship in the model.

Firm dynamics. Denote by E_{it} employment of establishment i in year t.[80] Job creation is the sum of net employment gains of expanding establishments and job destruction the sum of net employment losses of contracting establishments between two years,

$$JC_t = \frac{\sum_i \max\{E_{it} - E_{it-1}, 0\}}{0.5 \sum_i (E_{it} + E_{it-1})}, \qquad JD_t = \frac{\sum_i \max\{E_{it-1} - E_{it}, 0\}}{0.5 \sum_i (E_{it} + E_{it-1})}$$

Job reallocation is the sum of job creation and destruction, which can be decomposed into job creation and destruction of establishments that continue to be active and that due to establishment exit and entry,

$$\underbrace{JC_t + JD_t}_{\text{Job reallocation}_t} = \underbrace{JC_t^{incumbent} + JD_t^{incumbent}}_{\text{Incumbent job reallocation}_t} + \underbrace{JC_t^{entry} + JD_t^{exit}}_{\text{Establishment turnover}_t}$$

I alternatively construct unweighted measures of entry and exit as the count of entering and exiting establishments over the total count of establishments. I also compute firm entry as the share of employment at age zero firms and firm exit as the share of employment of exiting firms,[81] as well as unweighted measures of firm entry and exit.

GDP. To construct growth in state real GDP per worker, I convert nominal GDP to real GDP using regional CPIs from the BLS. Subsequently, I divide real GDP by the average of private sector employment in March in the current year and March in the subsequent year based on the BDS. Finally, I take the log difference of this to construct growth in state real GDP per worker. To construct growth in real GDP per labor force participant, I divided total real GDP by total labor

[79] This is the literal phrasing of the question. One would typically think that an individual only takes an action when she has no other better choice, which makes this phrasing somewhat confusing.

[80] Specifically, the BDS measures employment as those who were on the payroll in the pay period ending March 12.

[81] The BDS defines firm exit as an event when all establishments owned by a firm close down. It does not include exit due to a pure change of ownership.

force participants aged 16 and older from the CPS.

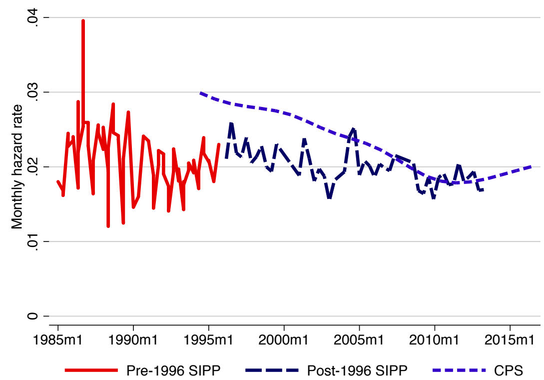
Worker dynamics. In the CPS and the SIPP, I define a worker as making an EU transition if she is employed in month t and unemployed in month $t+1$, and an UE transition if she is unemployed in month t and employed in month $t+1$. She makes a JJ transition if she is employed in month t and $t+1$ but with a different employer. I note that these definitions will lead to some time aggregation bias.[82] Based on this, I estimate the EU, UE and JJ hazard rates at time t as the fraction of employed or unemployed that undertakes one of these transitions between month t and $t+1$. All rates condition on the individual remaining in the labor force in month $t+1$. I focus my main analysis on workers who remain in the labor force to align with the theoretical analysis later. I show below that there has also been a decline in the hazard rate of exiting and entering the labor force over this period.

As noted above, the SIPP was redesigned in 1996, and as discussed by earlier authors this leads to an inconsistency in the JJ series in the 1995–1996 break (Nagypál, 2008; Mazumder, 2007).[83] In my baseline results, I do not make any adjustment for this. I have alternatively adjusted the pre-1996 series by first collapsing the JJ mobility rate by panel and wave (to avoid the issues with seam-bias discussed above) and then by year. I HP-filter the pre-1996 and post-1996 series individually using a smoothing parameter of 6.25, and compute an adjustment factor as the ratio of trend JJ in 1996 over trend JJ in 1995, $adj = JJ_{1996}/JJ_{1995}$. Finally, I adjust the pre-1996 series by this factor. Figure 9 plots the raw SIPP and CPS monthly JJ mobility series. The data are collapsed to the panel-wave frequency in the SIPP and the year level in the CPS.

[82]Recall may drive part of the measured EU and UE hazards (Fujita and Moscarini, 2017). Based on the limited evidence presented by these authors, there does not appear to be a strong time trend in the recall rate (see in particular their Tables A3–A4). I proceed under the assumption that accounting for recall would shift the hazard rates down but not bias the time trends.

[83]This does not appear to be an issue for the EU and UE hazard rates, because the question about monthly employment status is asked in a similar fashion pre and post the redesign.

FIGURE 9. MONTHLY UNADJUSTED JJ HAZARD IN THE SIPP, 1985–2013



Note: SIPP 1984–2013 and CPS 1994–2016. JJ: share of employed in month t who are employed with a different employer in $t+1$ (conditional on remaining in the labor force). Collapsed to panel-wave level in SIPP; year-level in CPS.

I also consider a third estimate of the EU and UE hazards based on the aggregate stock of employed, unemployed and short-term unemployed published by the BLS and the methodology of Shimer (2012),[84] which I sometimes refer to as the duration approach. Shimer (2012) outlines a flow-balance approach that allows him to estimate monthly EU and UE hazard rates based on the stock of employed, unemployed and short-term unemployed published by the BLS.[85] Specifically, denote by E_t, U_t and S_t the stock of employed, unemployed and short-term unemployed (less than four weeks), respectively. Suppose workers find and loose jobs at a monthly frequency, then the following flow balance equations relates the job finding rate, λ, and the separation rate, δ,

$$E_t = \lambda_t U_{t-1} + (1-\delta_t)E_{t-1}, \qquad S_t = \delta_t E_{t-1}$$

The second equation identifies δ_t, which implies that the first equation pins down λ_t. Shimer (2012) writes down a continuous-time system that allows him to adjust for time-aggregation. This, however, matters little for the secular trends and hence for simplicity I abstract from this.

Based on the establishment level data in the QWI, I define worker reallocation as the sum of hires and separations across all firms between two quarters. Churn as the difference between

[84]With the exception that I do not employ Shimer (2012)'s continuous time methodology to address time aggregation bias. Doing so complicates the analysis without changing the conclusions regarding the secular decline (the adjusted series is available on request and also in Shimer, 2012).

[85]These data are based on underlying CPS micro data, but the original micro data prior to 1967 has sadly been lost.

worker and job reallocation,

$$\text{Worker reallocation}_t \equiv \text{Job reallocation}_t + \text{Churn}_t \tag{21}$$

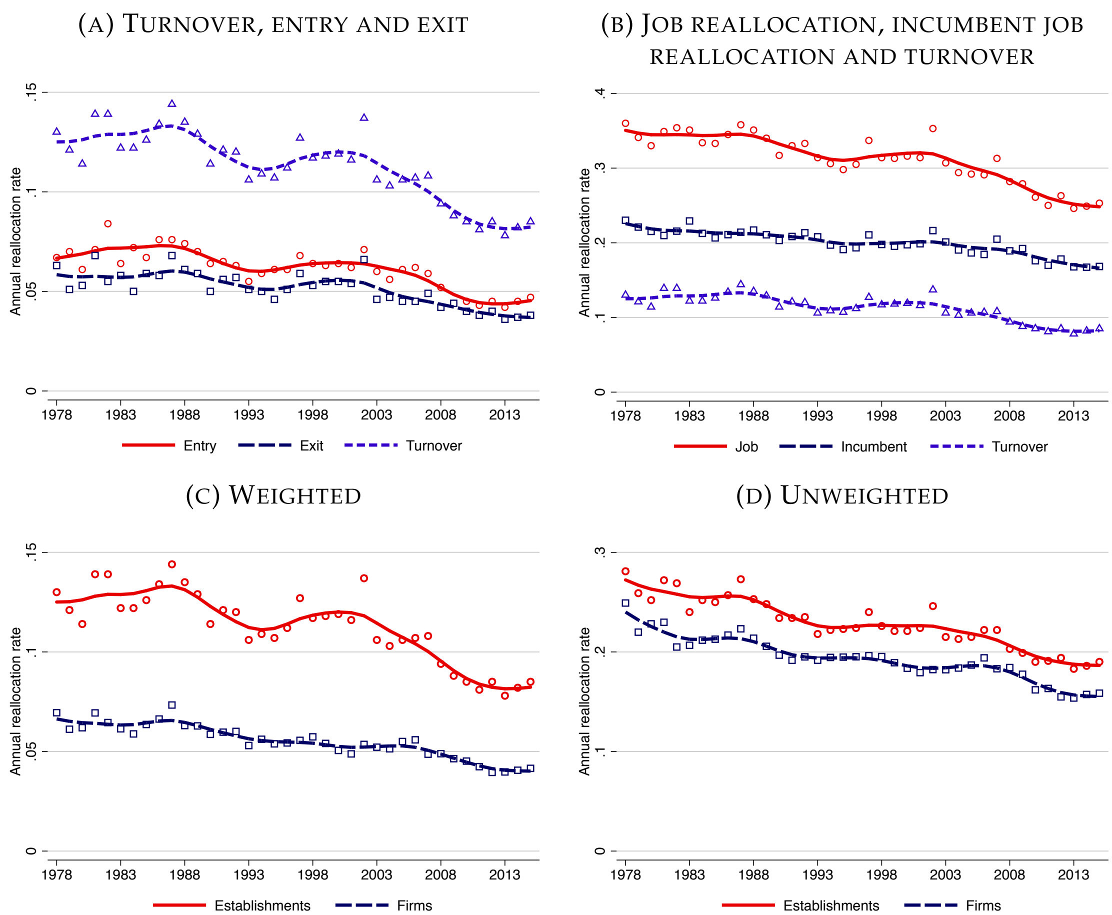
Churn may hence be thought of as replacement hiring—a worker left the firm but was replaced by a new worker so that the job stayed with the firm. The QWI only provides quarterly data. I aggregate these to the annual level as the unweighted quarterly average, and HP-filter the annual series with a smoothing parameter of 6.25.

B Additional Details on Facts

B.1 Business dynamism

The top left panel of Figure 10 illustrates that turnover of establishments has declined both because entry and exit have fallen. The top right panel shows that also a decline in job reallocation of incumbent firms has contributed importantly to the overall decline in job reallocation. The bottom left panel compares changes in firm turnover with establishment turnover, while the bottom right panel plots unweighted firm and establishment turnover. As is evident, dynamism has fallen across the board.

FIGURE 10. ANNUAL ESTABLISHMENT DYNAMICS, 1978–2015



Note: BDS 1978–2015. Private, non-agricultural employment. Weighted establishment turnover: job creation and destruction of entering and exiting establishments/firms divided by half the sum of employment in the prior and current year. Weighted firm turnover: sum of jobs created by age zero firms and jobs destroyed due to firm exit divided by total employment. Unweighted: count of exiting and entering establishments/firms divided by total count of establishments/firms. All measures are annual and HP-filtered with smoothing parameter of 6.25.

Table 9 summarizes the declines in firm dynamics. Job reallocation has fallen by 28 percent since 1986, and establishment entry and turnover by 38 percent. Instead focusing on firms leads to a similar conclusion: firm turnover has fallen by 39 percent and firm entry by 47 percent. The employment-weighted establishment and firm entry rate has declined by more than the unweighted rate, indicating that entering firms/establishments enter somewhat smaller now than 30 years ago. Yet also unweighted entry and turnover rates show notable declines.

TABLE 9. ESTABLISHMENT AND FIRM DYNAMICS, 1986–2015

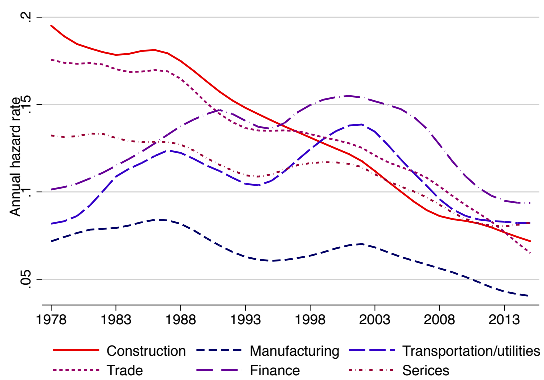
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Job reallocation			Turnover			Entry		
	1986	2015	% fall	1986	2015	% fall	1986	2015	% fall
Panel A: Establishments									
Weighted	0.345	0.248	-28.1	0.133	0.082	-37.9	0.073	0.045	-37.8
Unweighted				0.256	0.187	-27.2	0.142	0.101	-29.2
Panel B: Firms									
Weighted				0.065	0.040	-38.5	0.037	0.020	-46.6
Unweighted				0.214	0.155	-27.5	0.125	0.080	-36.1

Note: BDS 1978–2015. Private, non-agricultural employment. Job reallocation: sum of employment gains of expanding establishments and employment losses of contracting establishments; turnover: job creation and destruction of entering and exiting establishments/firms; entry: job creation of entrants. All measures are annual, expressed as rates by dividing by half the sum of employment in the prior and current year, and HP-filtered with smoothing parameter of 6.25.

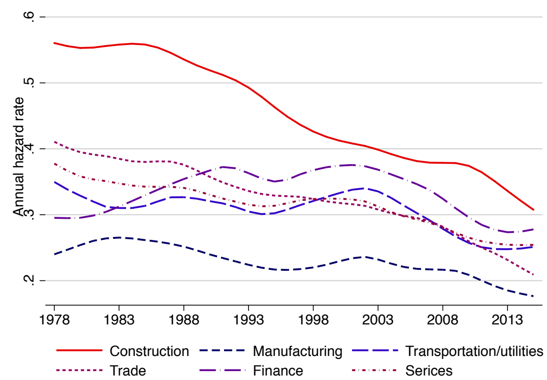
Firm dynamics by industry. The top left panel of Figure 11 plots establishment turnover by six aggregate sectors, while the top right panel does the same for overall job reallocation. Finance and to a lesser extent transportation and utilities displays a somewhat different trend, increasing for the first 20 years of the sample and then falling sharply in the last 15 years. Clearly there are important differences across sectors which future research may want to explore further. The bottom left panel plots the year effects from a regression of establishment turnover on year and sector dummies, while the bottom right panel does the same with job reallocation. Employment has if anything reallocated to sectors with *higher* reallocation rates, making the puzzle of the decline even larger.

FIGURE 11. REALLOCATION RATES BY INDUSTRY AND CONTROLLING FOR INDUSTRY, 1978–2015

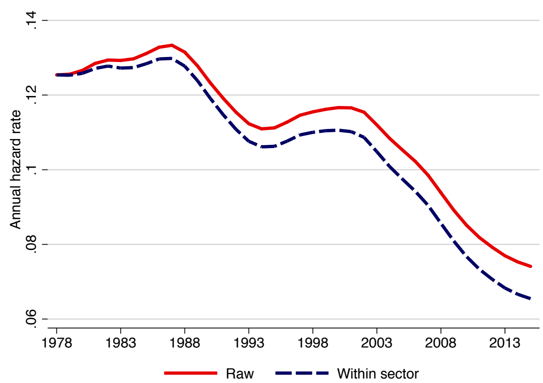
(A) TURNOVER



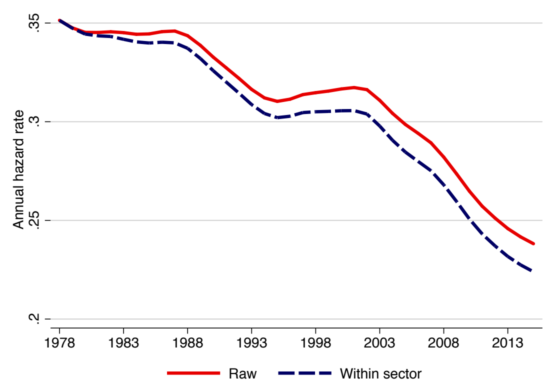
(B) JOB REALLOCATION



(C) TURNOVER



(D) JOB



Note: BDS 1978–2015. Private, non-agricultural employment. Job reallocation: sum of employment gains of expanding establishments and employment losses of contracting establishments; turnover: job creation and destruction of entering and exiting establishments/firms. All measures are annual, expressed as rates by dividing by half the sum of employment in the prior and current year, and HP-filtered with smoothing parameter of 6.25. Residual is the year effects from a regression of the reallocation rate on year and sector dummies.

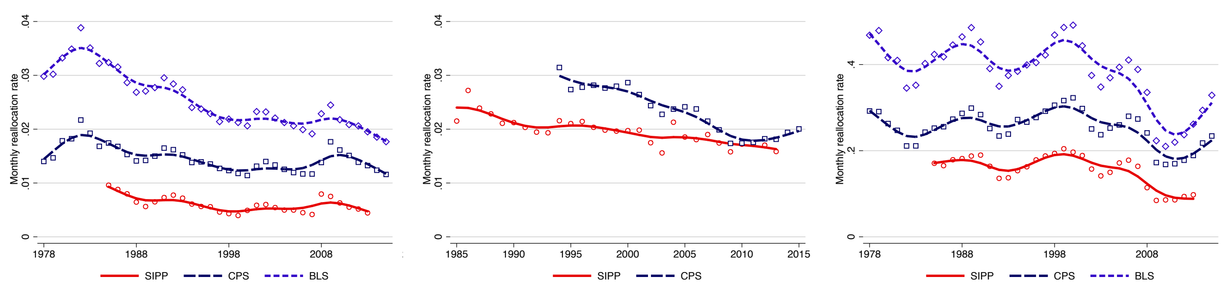
B.2 Labor market fluidity

Figure 12 plots the EU, JJ and UE hazard across the different data sources. The different data sources differ importantly in levels, which is the source of an existing literature. Shimer (2012) suggests that the duration approach may overestimate the UE hazard rate due to the implicit assumption that all unemployment spells end with a transition to employment. Furthermore, to the extent that some workers report being unemployed for less than four weeks when they enter unemployment from out of the labor force, this may explain the higher estimated EU hazard using the duration data. With respect to the difference between the SIPP and the CPS, Abowd and Zellner (1985) and Poterba and Summers (1986) argue that substantial classification error in respondents' employment status in the CPS as well as non-random sample attrition bias estimates of worker flows upwards.[86]

The more important take-away for my purposes is that the different data sources largely agree on the secular time trends. In particular, the EU hazard shows a large, secular decline over this period,[87] with the different data sources primarily disagreeing on the spike in the Great Recession,[88] Similarly, the JJ hazard displays a large decline over this period, which is larger in the CPS than the SIPP in the overlapping years.[89]

FIGURE 12. MONTHLY EU, JJ AND UE MOBILITY, 1978–2015

(A) EU (B) JJ (C) UE



Note: SIPP 1984–2013, BLS 1978–2015, CPS 1978–2015. Labor force age 16 and older. SIPP and CPS: EU hazard is the share of employed in month t who are unemployed in $t+1$; UE hazard is the share of unemployed in t who are employed in $t+1$; JJ hazard is the share of employed in month t who are employed at a different employer in $t+1$; all condition on remaining in the labor force. BLS: estimated from aggregate employment, unemployment and short-term unemployment following the method of Shimer (2012). The SIPP JJ series is adjusted for a break in 1996, see Appendix A for details. Average monthly rate during the year HP-filtered with smoothing parameter of 6.25.

Table 10 summarizes the declines in the various measures of worker mobility across the different data sources.

[86] These authors also develop methods to adjust the raw data. I do not pursue such an adjustment further, noting that the CPS displays both similar time trends and life cycle profiles (see the next section) as the SIPP. For the level of hazard rates, I rely on the SIPP.

[87] See also Davis (2008) for similar evidence of a large decline in job loss using initial unemployment insurance claims data.

[88] As noted by Shimer (2012), the greater increase in the micro data relative to the aggregate BLS data in the Great Recession may be due to particularly pronounced flows out of the labor force during that period.

[89] As I discuss in Appendix A, this measure is only available from the SIPP and CPS. Furthermore, the latter is only available from 1994, while the former is adjusted for a break in the series with the redesign of the SIPP in 1996. As such an adjustment involves a good amount of uncertainty, the resulting series should be interpreted cautiously.

TABLE 10. WORKER DYNAMICS, 1986–2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	EU			UE			JJ		
	1986	2015	% fall	1986	2015	% fall	1986	2015	% fall
BLS	0.031	0.018	-42.5	0.427	0.311	-27.0			
CPS	0.016	0.012	-29.0	0.259	0.224	-13.5	0.030	0.020	-34.2
SIPP	0.008	0.005	-44.2	0.174	0.088	-49.4	0.024	0.016	-32.0

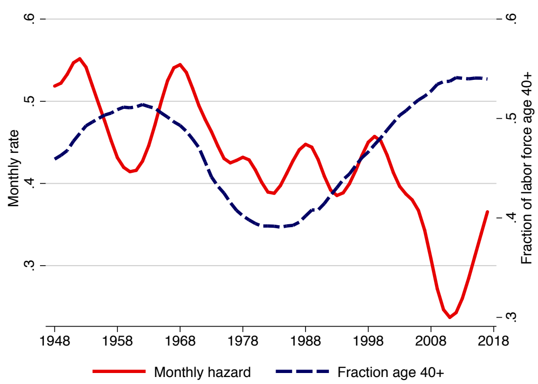
Note: SIPP 1984–2013, BLS 1978–2015, CPS 1978–2015. 1986 refers to 1994 for JJ in CPS and 2015 refers to 2013 in SIPP due to lack of data. Labor force age 16 and older. SIPP and CPS: EU hazard is the share of employed in month t who are unemployed in $t+1$; UE hazard is the share of unemployed in t who are employed in $t+1$; both condition on remaining in the labor force. BLS: estimated from aggregate employment, unemployment and short-term unemployment following the method of Shimer (2012). Average monthly rate during the year HP-filtered with smoothing parameter of 6.25.

A longer time series. Few nationally representative measures of dynamism are available prior to the late 1970s, but one can construct measures of EU and UE mobility back to 1948 following Shimer (2012).[90] Figure 13 plots the HP-filtered annualized monthly UE hazard (left) and EU hazard (right) in solid red and the share of the labor force 16 and older that is 40 years and older in dashed blue. The UE hazard possibly displays a secular decline, but it is hard to tell with the substantial business cycle volatility in this series. The EU hazard shows a strong negative time series correlation with the share of older ($\rho = 0.8$). Only a fraction of the covariation can be accounted for by the direct effect.

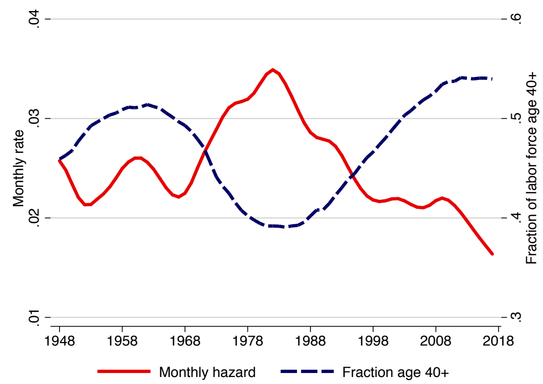
[90] These are clearly limited measures of dynamism. Yet Davis et al. (2010) find that long run changes in job loss of workers are positively correlated with changes in job destruction of firms using cross-industry data (I verify a similar positive correlation across states).

FIGURE 13. EU AND UE HAZARD AND THE SHARE OF OLDER, 1948–2017

(A) UE



(B) EU

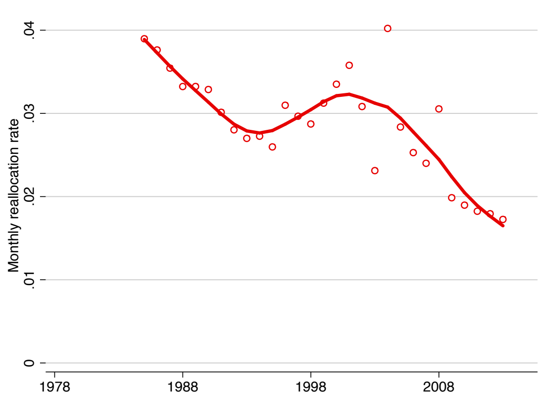


Note: BLS 1948–2017. Labor force age 16 and older. Monthly EU and UE hazards estimated based on the stock of employed, unemployed and short-term unemployed following the methodology of Shimer (2012). Share of labor force that is 40 years and older constructed as half of those age 35–45 plus everyone 45 and older. All series are seasonally adjusted, annualized and HP-filtered with smoothing parameter 6.25.

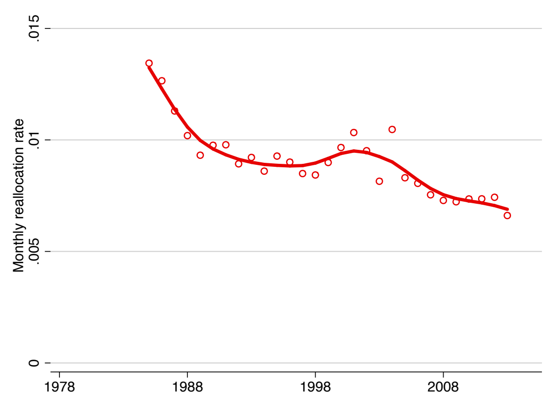
Flows in and out of the labor force Figure 14 plots monthly hazard rates of moving in and out of the labor force based on the SIPP. I do not compute these measures in the merged CPS micro data since earlier research has concluded that classification error leads to a particularly large bias in estimates of flows into and out of the labor force in the monthly CPS data (Nagypál, 2008). The NL hazard is substantially below the UE hazard, while the LN hazard is larger than the EU hazard. Both series display secular declines over this period.

FIGURE 14. MONTHLY FLOWS IN AND OUT OF THE LABOR FORCE, 1985–2013

(A) NL



(B) LN



Note: SIPP 1984–2013. NL: share of workers not in the labor force in month t who are in the labor force in month $t+1$; LN: share of individuals who are in the labor force in month t who are not in the labor force in month $t+1$. Average monthly rate during the year. HP-filtered with smoothing parameter of 6.25. See text for further details.

Linking worker reallocation to job reallocation Overall worker reallocation in period t equals the sum of workers flowing in and out of unemployment, in and out of the labor force, and directly between employers,

$$worker_t = eu_t + ue_t + nl_t + ln_t + 2 * jj_t$$

where lower letters represent the number of workers (as distinct from the hazard rate). From an accounting perspective, overall worker reallocation consists of job reallocation and *churn*, i.e. worker reallocation over an above what is necessary to account for job flows,

$$worker_t = job_t + churn_t$$

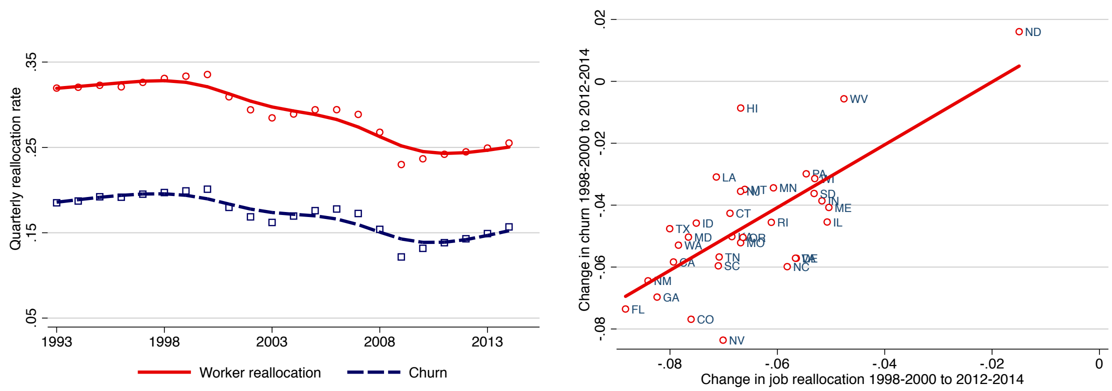
The left panel of Figure 15 plots the secular trend in quarterly job reallocation and churn based on the QWI for 1993–2014. As noted above, the data are only available back to 1993 and only a limited number of states provide data that far back. Furthermore, the data are at the EIN level, which differs in subtle ways from establishments or firms. Nevertheless, taken at face value the figure suggests that the decline in job reallocation only accounts for about half of the decline in worker reallocation over this period, with a large fall also in churn.

To what extent is the decline in worker reallocation that cannot directly be traced back to firm dynamics driven by factors distinct from those that have led to declining job reallocation? The right panel of Figure 15 plots the within-state change in job reallocation between 1998–2000 and 2012–2014 on the x-axis against the within-state change in churn over the same period on the y-axis across U.S. states. Only 32 states provide data back to 1998 and I cannot meaningfully go back earlier than that due to a lack of data. The strong correlation between secular changes in job reallocation and churn across U.S. states may be interpreted as a common factor leading to declines in both rates.

Figure 15. Worker reallocation and churn, 1993–2014

(a) Job reallocation and churn

(b) Linking declines across states

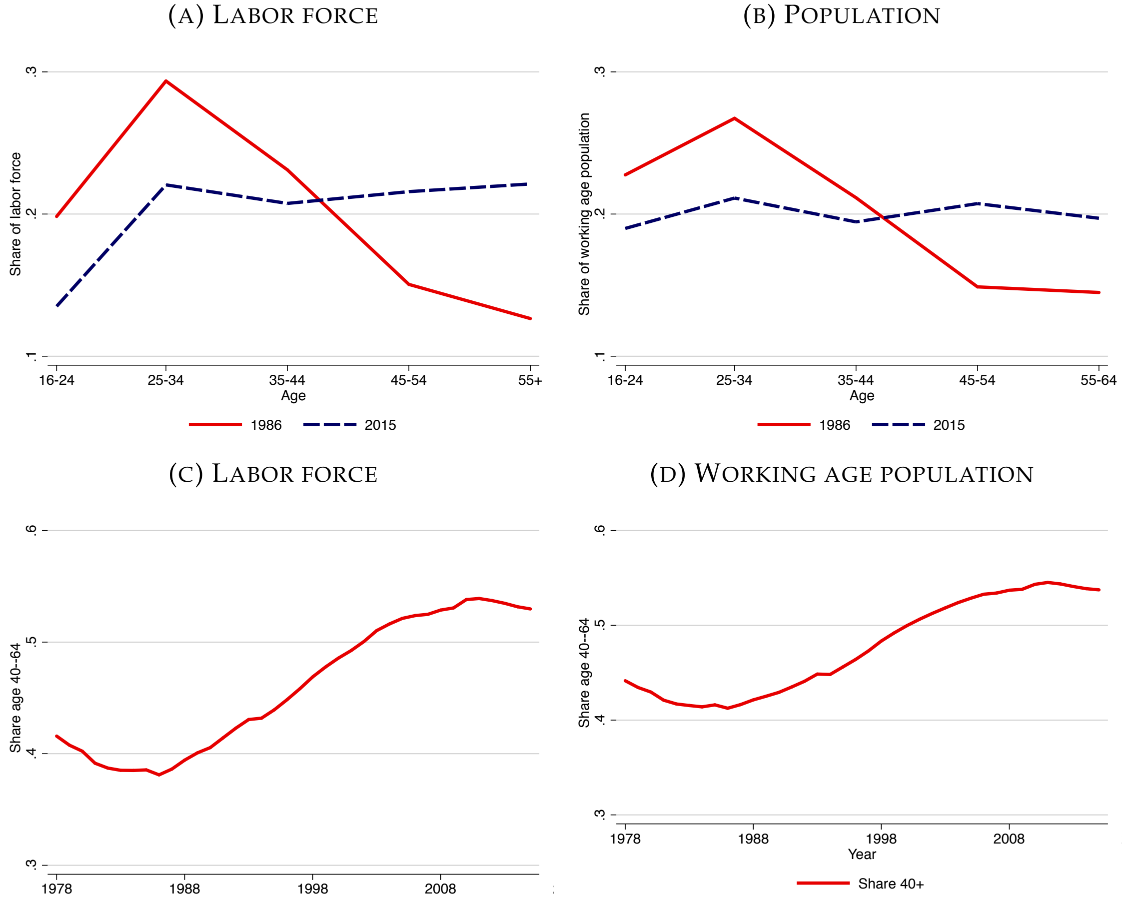


Note: QWI 1993–2014 and BDS 1998–2014. Private, state and local employment (QWI), private employment (BDS). Job reallocation: sum of employment gains of expanding establishments (EINs) and employment losses of contracting establishments (EINs); worker reallocation: sum of hires and separations; churn: difference between worker reallocation and churn.

B.3 Aging

The top left panel of Figure 16 plots the age composition of the the labor force age 16 and older, and the top right panel the age composition of the population age 16–64. Although labor force participation differs systematically by age so that the levels are somewhat different, the change over time is similar. The bottom two panels illustrate this by plotting the share of the labor force (left) or population (right) age 19–64 that is 40–64 from 1978–2015. The majority of the increase in the share of older over this period is due to population aging, not differential trends in labor force participation by age.

FIGURE 16. AGE COMPOSITION OF THE U.S. LABOR FORCE/POPULATION 1978–2015

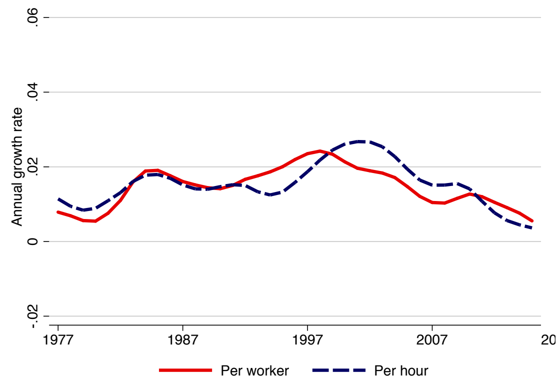


Note: BLS, Intercensal Censi and CPS 1978–2015. Top left: total number of labor force participants of the given age group relative to the total labor force age 16 and older; Top right: total number of individuals of the given age group relative to the total population 16–64; Bottom left: share of labor force participants age 19–64 that is 40–64; Bottom right: share of population age 19–64 that is 40–64.

B.4 Growth

Figure 17 plots the HP-filtered annual growth rate in real GDP per worker and per hour since 1971. Growth was notably high in the late 1990s driven by rapid advanced in IT technology. As noted by other authors (Fernald, 2014), the growth rate appears to show a decline starting in the early 2000s.

FIGURE 17. GROWTH IN REAL GDP



Note: OECD. Annual data HP-filtered with smoothing parameter of 6.25.

B.5 Life cycle mobility and the direct effect of aging

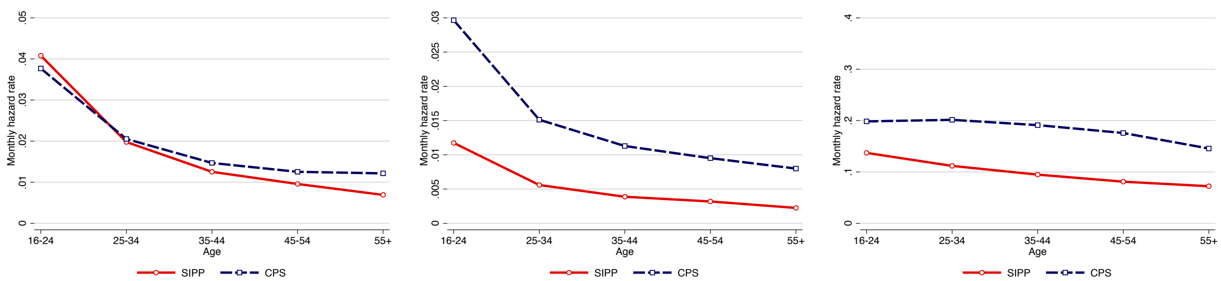
This section provides additional empirical facts on life cycle individual mobility.

Worker mobility. Figure 18 compares estimated life cycle profiles of worker mobility in the CPS and the SIPP.[91] The data sources largely agree on both the level and the shape of the JJ hazard in the left panel. The probability of a JJ move falls from around four percent per month for young workers to around one percent for older workers, with a slightly more pronounced fall in the SIPP. The level of the EU hazard is substantially larger in the CPS than the SIPP, as can be seen in the middle panel. As discussed in the previous section, this is likely at least part due to well-documented issues with classification error inflating gross worker flows in and out of unemployment in the CPS. Both data sources agree on the life cycle shape: young workers are roughly three times as likely to experience an EU transition relative to older workers. The right panel shows that the UE hazard displays a less pronounced life cycle profile.

[91] I consistently present results aggregated to these five age groups to be consistent with the subsequent analysis of the indirect effects of aging in Section 7. Results by more disaggregated age groups are similar and available on request. Given the high number of observations, the means are tightly estimated and I do not include confidence intervals in the graphs to avoid clutter.

FIGURE 18. WORKER MOBILITY OVER THE LIFE CYCLE

(A) JJ (B) EU (C) UE



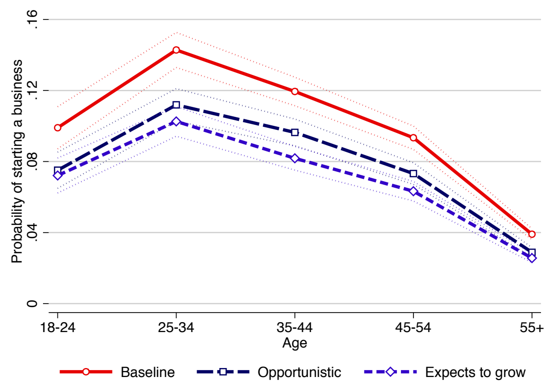
Note: SIPP 1984–2013, CPS 1978–2015. Labor force age 16 and older. EU hazard: share of employed in month t who are unemployed in $t + 1$; UE hazard: share of employed in month t who are unemployed in $t + 1$; JJ hazard: share of employed in t who are employed in $t + 1$ but with a different employer; both condition on remaining in the labor force. Weighted using the provided survey weights. Pooled data across all years adjusted such that the average matches that in 2012–2013.

Entry to entrepreneurship. To study the life cycle profile of entry into entrepreneurship, I follow Liang et al. (2016) to use data from the GEM. Figure 19 plots the entry rate into entrepreneurship by age. In solid red with circles is the baseline, while the long-dashed navy blue series with squares additionally conditions on those that report that they started the business to take advantage of a business opportunity. Finally the short-dashed royal blue series with diamonds additionally conditions on those that expect to hire at least one person over the next five years.

In all cases, entrepreneurship rises at young ages to peak at around age 30, and subsequently falls monotonically with age.[92] In line with findings in Hurst and Pugsley (2011), a non-trivial share of those that enter do not expect to grow their enterprise, but focusing on those that expect to add workers provides a similar conclusion with respect to the life cycle pattern of entry (instead conditioning on expecting to add five or 10 employees provides a similar conclusion).

[92]This should not be confused with the *level* of entrepreneurship, which displays a monotonically increasing, concave profile with age. I will argue later that entry to entrepreneurship plays a special role in driving firm dynamics and economic growth, which motivates the focus on entry as distinct from the level of entrepreneurship.

FIGURE 19. ENTREPRENEURSHIP OVER THE LIFE CYCLE



Note: GEM 2001–2010. Share of population who are active in the management of a startup that has paid owners' salaries and wages for at most 42 months and who own all or part of the enterprise. Opportunistic: additionally conditions on having entered to take advantage of a business opportunity (in contrast to not having a better choice for work). Expects to grow: additionally conditions on expecting to employ at least one person (plus the owner) in five years. The GEM does not provide data on individuals younger than 18. Weighted by the provided survey weights. Dotted lines are 95% confidence intervals.

The direct effect of aging. To estimate the importance of the direct effect over this period, I first compute age-conditional JJ, EU and UE mobility rates as well as entrepreneurship entry rates in a late period.[93] Denote these coefficients on the respective age groups in the late period by β^a_{late}. Subsequently, I compute the reallocation rate that would result from only changes in the age composition as $\widehat{rate}_{\text{period}} = \sum_a \beta^a_{\text{late}} share^a_{\text{period}}$, where $share^a_{\text{period}}$ is the share of the labor force that is in age group a in that period. The direct effect of aging equals $\widehat{rate}_{\text{late}} - \widehat{rate}_{\text{early}}$. Throughout this paper, I use as base period a late period due to better data availability at the end of my sample period and in this sense run all exercises "backwards."

The mechanical effect of aging accounts for 23–27 percent of the change in JJ and EU mobility, less of the recent fall in UE mobility (but as noted above this decline is likely at least partly a business cycle phenomenon), and 18–19 percent of the change in entry over this period.[94] Table 11 summarizes the estimated direct effect of aging on JJ, EU and UE mobility as well as firm start-up rates.

[93]Specifically, I use the SIPP in 2011–2013, the CPS in 2015, and the GEM in 2001–2010. I pool all years in the GEM due to the relatively small sample size and normalize the entry rate to match the level in 2010.

[94]For comparison, Hyatt and Spletzer (2013) find that the direct effect of aging accounts for 9–23 percent of changes in worker mobility in the LEHD and CPS between 1998–2010. The reason I attribute a somewhat larger direct effect is likely due to the sample period. These authors start in 1998, after the baby boomers have mostly moved out of the young age groups characterized by very high mobility, and stop in the midst of the Great Recession, when the raw series is likely depressed below trend.

TABLE 11. DIRECT EFFECT OF AGING ON DYNAMISM, 1986–2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early		Late		% change		
	Raw	Direct	Raw	Direct	Raw	Direct	Share
Panel A: JJ mobility							
SIPP	0.024	0.019	0.017	0.017	45.4	12.3	27.1
Panel B: EU mobility							
SIPP	0.009	0.006	0.005	0.005	61.3	14.0	22.9
CPS	0.017	0.015	0.012	0.014	42.0	10.7	25.6
Panel C: UE mobility							
SIPP	0.175	0.101	0.090	0.093	94.5	8.6	9.1
CPS	0.251	0.199	0.221	0.196	13.7	1.9	13.9
Panel D: Entry to entrepreneurship							
Baseline	156.5	109.9	100	100	56.5	9.9	17.5
Opportunistic	156.5	110.0	100	100	56.5	10.0	17.7
Expect to grow	156.5	110.8	100	100	56.5	10.8	19.2

Note: SIPP 1984–2013, CPS 1978–2015, GEM 2001–2010, BDS 1978–2015. Labor force age 16 and older. Early refers to 1986, late to 2013 in the SIPP and 2015 in the CPS and for the entrepreneurship rates. % change is $100 * (early/late - 1)$. EU: share of employed in month t who are unemployed in $t+1$; UE: share of unemployed in month t who are employed at $t+1$; JJ: share of employed in t who are employed in $t+1$ but with a different employer; all condition on remaining in the labor force. Baseline: share who started a firm in the past 42 months; opportunistic: additionally conditions on having started the firm to take advantage of a perceived business opportunity; growth: additionally conditions on expecting to add at least one worker over the next five years; raw entry rate is the unweighted firm entry rate in the BDS; all entry rates are normalized to 100 in the late period. Direct effect estimated based on a shift-share methodology, raw data is annual and HP-filtered with smoothing parameter of 6.25. See text for further details.

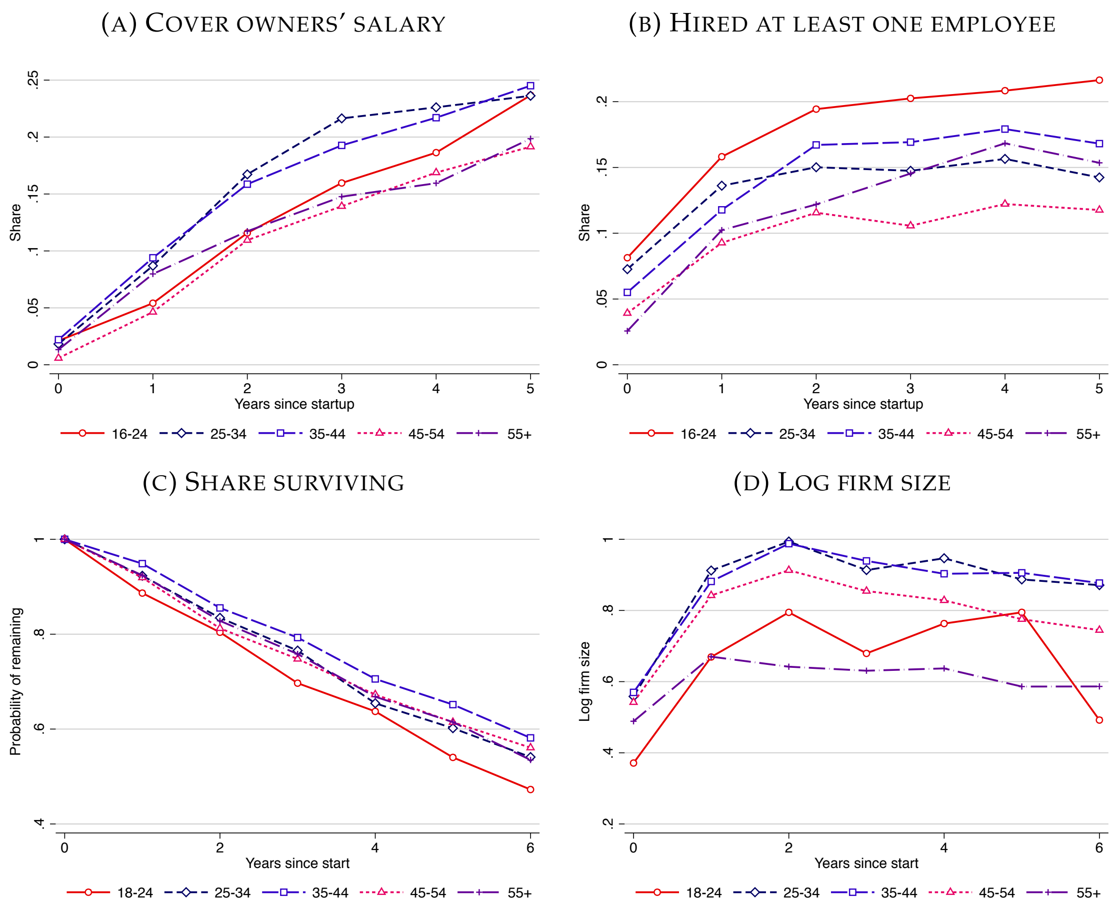
Post-entry performance by age of founder. To understand the importance of aging for aggregate economic outcomes through the entrepreneurship channel, more than the life cycle profile of entry arguably matters. Figure 20 investigates the relationship between the age of the founder of a firm at the time of its inception and its subsequent performance based on the KFS and PSED. The top left panel plots the share of startups that have evolved to cover the founders' salaries for up to five years after entry based on the PSED.[95] The top right panel plots the share of active startups in year t that have hired at least one employee based on the PSED (the survey does not ask a more detailed firm size question). The bottom left panel plots the share of start-ups in year 0 that remain active up to seven years after entry based on the KFS.[96] Finally, the bottom right panel plots average log

[95] To avoid clutter, I exclude confidence intervals from the graphs, but differences across age groups are in most cases not statistically significant.

[96] The exit rate is lower than in the BDS and it shows no evidence of declining with the age of the firm, in contrast to the BDS. These discrepancies may be due to contemporaneous time effects given that the first few years cover the pre-Great Recession boom and the last few years the subsequent large bust. It is not clear to what extent this may differentially affect firms depending on the age of its founder and the results should be interpreted with this caveat in

firm size (plus one) of active start-ups in year t. These graphs generally provide little evidence of any pronounced, systematic differences in post-entry performance by age of the founder.

FIGURE 20. STARTUP DYNAMICS BY AGE OF FOUNDER



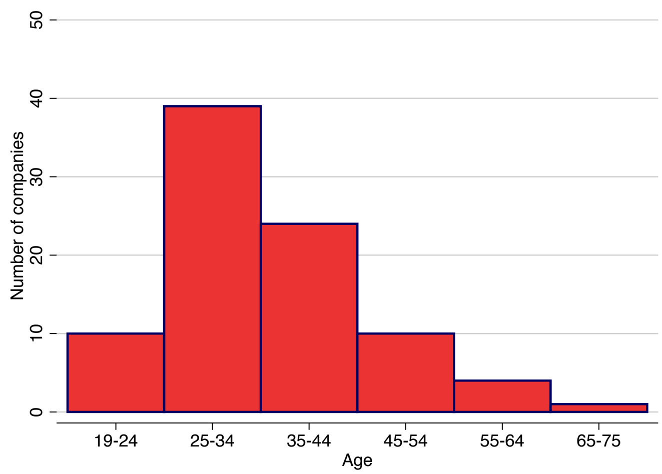
Note: Top graphs use the PSED 2005–2010, bottom graphs the KFS 2004–2010. Top left: share of all start-ups in year 0 that have evolved to cover owners' salaries; top right: share of all start-ups that remain active in year t that has hired at least one worker; bottom left: share of all start-ups in year 0 that remains active; bottom right: average log number of employees plus one of start-ups that remain in year t. All measures broken down by the age of the founder(s) at the time of inception of the firm in year 0 (average age in case of multiple founders). The KFS starts at age 18. Weighted by the provided survey weights.

Founders of S&P100 companies. If young entrepreneurs engage in a lengthy period of trial and error before they come up with a viable business idea, one may expect this to be reflected in the age distribution of the founders of current, successful companies. Figure 21 investigates this by plotting the companies in the S&P100 index by the age of their founder at time of inception. These are some of the largest and most established companies in the U.S., representing over half of mar-

mind.

ket capitalization in the U.S. Although it does not account for the underlying age distribution of the population at the time of inception, Figure 21 appears at odds with the hypothesis that a prolonged period of unsuccessful entrepreneurship is required before founding a highly successful company.

FIGURE 21. NUMBER OF S&P100 COMPANIES BY AGE OF FOUNDER AT TIME OF INCEPTION

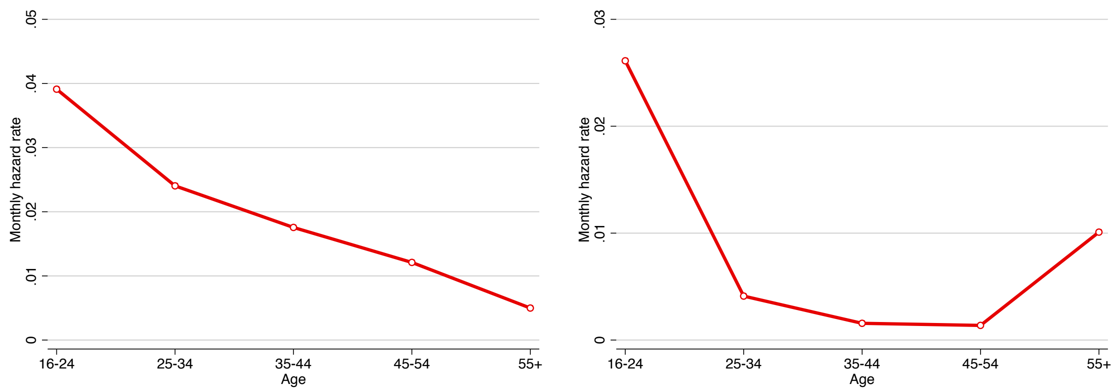


Note: Author's calculations. S&P100 companies with an identified founder binned by the age of the founder at the time of inception. In case of multiple founders, a company is represented by the average age of the founders. In case the traded company was created through a merger or acquisition, it is the average age of the original, purchasing company (or the average age of the constituent companies in case of a merger). The final data contains 88 companies with identified founders.

NL and LN flows over the life cycle. The left panel of Figure 22 plots the hazard rate of entering the labor force from not in the labor force and the right panel the hazard rate of exiting the labor force. Given that an earlier literature has documented that flows in and out of the labor force suffer particularly from the classification error in the CPS, I only compute the latter two series in the SIPP (Nagypál, 2008).

FIGURE 22. NL AND LN MOBILITY OVER THE LIFE CYCLE

(A) NL (B) LN



Note: SIPP 1984–2013. Labor force age 16 and older. NL: share of NILF in month t who are in the labor force in $t+1$; LN: share of the labor force in month t who are NILF in $t+1$. Weighted using the provided survey weights. Pooled data across all years adjusted such that the average matches that in 2012–2013.

B.6 Direct effect of firm aging

Table 12 summarizes the direct effect of firm aging on the exit rate and incumbent job reallocation. The shift towards older firms accounts for a substantial share of the declines in dynamism, including 25 percent of the fall in incumbent job reallocation, 42 percent of the decline in establishment exit and a full 78 percent of the decline in firm exit. Of course, this is in a pure accounting sense: there is no reason to not expect a change in age-conditional behavior of firms over this period.

TABLE 12. DIRECT EFFECT OF FIRM AGING ON DYNAMISM, 1989–2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early		Late		% change		
	Raw	Direct	Raw	Direct	Raw	Direct	Share
Panel A: Establishment dynamics							
Incumbent	0.213	0.181	0.168	0.170	27.0	6.8	25.1
Exit	0.058	0.047	0.037	0.038	54.9	22.9	41.7
Exit (unweighted)	0.103	0.088	0.074	0.076	39.8	15.2	38.2
Panel B: Firm dynamics							
Exit (firms)	0.031	0.030	0.021	0.022	48.8	38.1	78.1
Exit (unweighted, firms)	0.079	0.073	0.063	0.065	25.4	12.9	50.6

Note: BDS 1988–2014. Labor force age 16 and older. Early refers to 1986, late to 2013 in the SIPP and 2015 in the CPS and for the entrepreneurship rates. % change is $100 * (early/late - 1)$. EU: share of employed in month t who are unemployed in $t+1$; UE: share of unemployed in month t who are employed at $t+1$; JJ: share of employed in t who are employed in $t+1$ but with a different employer; all condition on remaining in the labor force. Baseline: share who started a firm in the past 42 months; opportunistic: additionally conditions on having started the firm to take advantage of a perceived business opportunity; growth: additionally conditions on expecting to add at least one worker over the next five years; raw entry rate is the unweighted firm entry rate in the BDS; all entry rates are normalized to 100 in the late period. Direct effect estimated based on a shift-share methodology, raw data is annual and HP-filtered with smoothing parameter of 6.25. See text for further details.

C Additional Details on Model

C.1 Stylized example

This section considers a simple example that illustrates a key implication of combining creative destruction with on-the-job search in a frictional labor market. For that purpose, I abstract for now from life-cycle considerations and assume that a unit mass of infinitely lived workers may be employed by low or high productivity firms. Entrepreneurs enter as high productive and attempt to hire workers (I assume for simplicity that only entrants may hire). High-productive firms become low-productive at rate π, and workers find new jobs at rate λ. I treat π and λ as exogenous for now and will endogenize them later.

Denote by V_1 and V_2 the value of a match between a worker and a firm with low and high productivity, respectively. Bargaining takes place as in Cahuc et al. (2006) with worker bargaining power β (this is explained in greater detail in the next section), so that the value functions solve

$$\rho V_1 = p_1 + \lambda\beta\left(V_2 - V_1\right), \qquad \text{and} \qquad \rho V_2 = p_2 + \pi\left(V_1 - V_2\right)$$

At rate λ a worker employed in a low-productive job finds a high-productive job, in which case he gets the full value of his current match plus a slice β of the differential surplus. At rate π a high-productive job becomes low-productive.

Let F_1 denote the fraction of workers in low productivity jobs. It is characterized by a simple flow-balance equation whose solution is $F_1 = \frac{\pi}{\pi+\lambda}$. Based on this and a solution to the Bellman equations, the value of a job can be written as

$$J = qF_1(1-\beta)(V_2 - V_1) = q(1-\beta)\frac{\pi}{\pi+\lambda}\frac{1}{\rho+\lambda\beta+\pi}(p_2 - p_1) \tag{22}$$

At for now exogenous rate q the job contacts a worker, who is employed in a low-productive job with probability F_1. In this case, the entrant firm successfully recruits a worker and gets a slice $1-\beta$ of the differential surplus, while in all other cases the payoff is zero.

Three things are worth noting: First, a higher turnover rate of firms increases labor market mismatch, $\partial F_1/\partial\pi > 0$. Second, a higher turnover rate increases job-to-job mobility, since less well-matched workers are more likely to accept a new job offer, $\partial JtJ/\partial\pi = \partial(\lambda F_1)/\partial\pi > 0$. Finally, the impact of higher turnover on the value of a job—and hence job creation—is ambiguous due to two offsetting effects. On the one hand, the match falls behind in productivity faster, which lowers the value of entering—a *duration effect*. On the other hand, it makes the labor market more mismatched, which increases the value of entering—a *mismatch effect*. In this simplified example, the following inequality characterizes the tradeoff,

$$\frac{\partial J}{\partial \pi} > 0 \iff \lambda\rho + \lambda^2\beta > \pi^2 \tag{23}$$

In the full-fledged model developed below, the drift in firm productivity, π, equals the growth rate of the economy. $\rho > \pi$ is necessary to ensure that the problem is meaningful.[97] The on-the-job job finding rate is typically estimated to be greater than the growth rate of the economy, $\lambda > \pi$, while $\beta \in [0,1]$. This suggests that the inequality (23) may be satisfied and the value of entering increasing in the turnover rate. Regardless of whether parameter values are such that (23) holds, however, the more general insight from this stylized example is that in an environment with creative destruction and on-the-job search, the duration effect of higher growth on the value of entering is moderated by a labor market mismatch effect.[98] The quantitative general equilibrium

[97]Strictly speaking, π is the growth rate due to selection. To the extent that also incumbent firms contribute to growth, an even stricter requirement is necessary to ensure that the problem does not explode.

[98]In contrast, the models in Aghion and Howitt (1994) and Mortensen and Pissarides (1998) feature job creation/entry

model I develop below embeds this intuition into a life-cycle model of firm and worker dynamics.

C.2 Value of match with known productivity

$$\begin{aligned}
\rho V(z,x,a) =& e^z x \underbrace{- \mu \frac{\partial V(z,x,a)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 V(z,x,a)}{\partial z^2}}_{\text{Shocks to } z} + \underbrace{\kappa(a)\left[\max\left\{V(z,x,a+1), U(a+1)\right\} - V(z,x,a)\right]}_{\text{Worker ages}} + \\
& \underbrace{+ \lambda\beta \int_0^\infty \max\left\{V(z',x_u,a) - V(z,x,a), 0\right\} dF(z') +}_{\text{New job offer}} \\
& \underbrace{+ \nu(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - V(z,x,a) + U(a), 0\right\} d\Omega(c)}_{\text{Entrepreneurship opportunity}}
\end{aligned}$$

C.3 Individual's value function and wage policies

Denote by $W^w(z,x,a,w)$ the value to a worker with productivity x and age a working for a firm with productivity z while being paid wage w, again with the convention that $W^w(z,x_u,a,w)$ denotes the expected value for a worker with unknown productivity. It solves the recursion

that may be increasing in the growth rate as a result of a capitalization effect and the option to upgrade technology, respectively, with neither of them studying the effect of on-the-job search.

$$
\begin{aligned}
\rho W^{w}\left(z, x_u, a, w\right) = & w \underbrace{- \mu \frac{\partial W^{w}\left(z, x_u, a, w\right)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2} \frac{\partial^2 W^{w}\left(z, x_u, a, w\right)}{\partial z^2}}_{\text{Shocks to } z} + \\
& + \underbrace{\kappa(a)\left[\max\left\{\min\left\{W^{w}(z, x_u, a+1, w), V(z, x_u, a+1)\right\}, U(a+1)\right\} - W^{w}\left(z, x_u, a, w\right)\right]}_{\text{Worker ages}} + \\
& + \underbrace{\lambda \int_{0}^{z} \max\left\{V\left(z', x_u, a\right) + \beta\left[V\left(z, x_u, a\right) - V\left(z', x_u, a\right)\right] - W^{w}(z, x_u, a, w), 0\right\} dF(z')}_{\text{Worse job offer}} + \\
& + \underbrace{\lambda \int_{z}^{\infty} \left\{V\left(z, x_u, a\right) + \beta\left[V\left(z', x_u, a\right) - V\left(z, x_u, a\right)\right] - W^{w}(z, x_u, a, w)\right\} dF(z')}_{\text{Better job offer}} + \\
& + \underbrace{\psi \sum_{i \in \{b, g\}} \pi(x_i) \max\left\{\min\left\{W^{w}(z, x_i, a, w), V(z, x_i, a)\right\}, U(a)\right\} - W^{w}(z, x_u, a, w)}_{\text{Worker's productivity is revealed}} + \\
& + \underbrace{\nu(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - W^{w}\left(z, x_u, a, w\right) + U(a), 0\right\} d\Omega(c)}_{\text{Entrepreneurship opportunity}}
\end{aligned}
$$

When a worker meets a new potential employer, I impose the bargaining protocol. For the other continuation values, the assumption is that if one party has a credible threat to abandon the renegotiation takes place to avoid a bilaterally inefficient separation. The outcome of such renegotiation is assumed to leave the party who initiated the renegotiation with zero surplus from the match. For instance, if the worker ages and would prefer to be unemployed at a given wage w when in fact there are positive gains from trade, renegotiation takes place such that the worker gets exactly her outside option and is willing to remain in the match. Similarly, if in this case the firm would have preferred to fire the worker rather than pay wage w, renegotiation takes place such that the firm is indifferent between firing the worker and remaining in the match. Allowing for such renegotiation is necessary to ensure that the value of the match does not depend on the way the value is split.

$$
\begin{aligned}
\rho W^w(z,x,a,w) =& w - \underbrace{\mu \frac{\partial W^w(z,x,a,w)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2} \frac{\partial^2 W^w(z,x,a,w)}{\partial z^2}}_{\text{Shocks to } z} + \\
& + \underbrace{\kappa(a)\left[\max\left\{\min\left\{W^w(z,x,a+1,w), V(z,x,a+1)\right\}, U(a+1)\right\} - W^w(z,x,a,w)\right]}_{\text{Worker ages}} + \\
& + \underbrace{\lambda \int_0^{\underline{z}^e(x,a)} \max\left\{V(z',x_u,a) + \beta\left[V(z,x,a) - V(z',x_u,a)\right] - W^w(z,x,a,w), 0\right\} dF(z')}_{\text{Worse job offer}} + \\
& + \underbrace{\lambda \int_{\underline{z}^e(x,a)}^{\infty} \left\{V(z,x,a) + \beta\left[V(z',x_u,a) - V(z,x,a)\right] - W^w(z,x,a,w)\right\} dF(z')}_{\text{Better job offer}} + \\
& + \underbrace{\nu(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - W^w(z,x,a,w) + U(a), 0\right\} d\Omega(c)}_{\text{Entrepreneurship opportunity}}
\end{aligned}
$$

Based on this, I can define the wage an unemployed receives when starting at a firm z, $w_u(z,a)$, as

$$W^w(z,x,a,w_u(z,a)) = U(a) + \beta\left[V(z,x_u,a) - U(a)\right]$$

The wage of a worker employed at z with productivity x who receives a competing offer z' that is not better than the current match receives updated wage $w_s(z,x,a,z')$ with the old firm, where

$$W^w(z,x,a,w_s(z,x,a,z')) = V(z',x_u,a) + \beta\left[V(z,x,a) - V(z',x_u,a)\right]$$

subject to the natural constraint that the worker cannot be worse off with his current firm from receiving a new offer. That is, his updated wage is $\max\left\{w, w_s(z,x,a,z')\right\}$. A worker who receives a better offer z' receives wage $w_m(z,z',x,a)$ with the new firm, where

$$W^w(z',x_u,a,w_m(z,x,a,z')) = V(z,x,a) + \beta\left[V(z',x_u,a) - V(z,x,a)\right]$$

Finally, I need to specify adjustments to wages that ensures that all separations are bilaterally optimal. In cases where either the firm's or worker's participation constraint becomes binding, I assume that wages adjust such that the party with a binding constraint is indifferent between remaining in the match and quitting it. Hence, a worker who receives an entrepreneurship opportunity that is not worth pursuing potentially receives an updated wage $w_e(z,x,a,c)$ to ensure that he only enters entrepreneurship when it is bilaterally efficient, where $W^w(z,x,a,w_e(z,x,a,c)) = E - c + U(a)$. When a worker would rather quit to unemployment, he receives updated wage $w_r(z,x,a)$, where $W^w(z,x,a,w_r(z,x,a)) = U(a)$. Finally when a firm would rather lay off a worker at the given wage (but such a layoff would not be bilaterally optimal), the worker receives adjusted wage $w_f(z,x,a)$ such that $W^w(z,x,a,w_f(z,x,a)) = V(z,x,a)$.

C.4 Firm's value function and value of match

Denote by $W^f(z,x,a,w)$ the value to a firm with productivity z of a match with productivity x with a worker of age a when the worker is paid w, again with the convention that $W^f(z,x_u,a,w)$ denotes the value when match productivity is unknown. The value when match productivity is unknown solves the recursion,

$$
\begin{aligned}
\rho W^f(z,x_u,a,w) = {} & e^z - w - \underbrace{\mu \frac{\partial W^f(z,x_u,a,w)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 W^f(z,x_u,a,w)}{\partial z^2}}_{\text{Shocks to } z} + \\
& + \underbrace{\kappa(a)\left[\max\left\{\min\left\{W^f(z,x_u,a+1,w), V(z,x_u,a+1) - U(a+1)\right\},0\right\} - W^f(z,x_u,a,w)\right]}_{\text{Worker ages}} + \\
& + \underbrace{\lambda \int_0^z \left[V(z,x_u,a) - \max\left\{V(z',x_u,a) + \beta\left[V(z,x_u,a) - V(z',x_u,a)\right], W^w(z,x_u,a,w)\right\} - W^f(z,x_u,a,w)\right] dF(z')}_{\text{Worker gets worse job offer}} + \\
& - \underbrace{\lambda(1-F(z))W^f(z,x_u,a,w)}_{\text{Worker gets better job offer}} + \underbrace{\psi \sum_{i\in\{b,g\}} \pi(x_i)\max\left\{\min\left\{W^f(z,x_i,a,w), V(z,x_i,a) - U(a)\right\},0\right\} - W^f(z,x_u,a,w)}_{\text{Worker's productivity is revealed}} + \\
& + \underbrace{\nu(a)\int_{\bar{c}^e(z,x_u,a)}^{\bar{c}} V(z,x_u,a) - \max\left\{E - c + U(a), W^w(z,x_u,a,w)\right\} - W^f(z,x_u,a,w)\, d\Omega(c)}_{\text{Worker gets bad entrepreneurship opportunity}} - \underbrace{\nu(a)\Omega\left(\bar{c}^e(z,x_u,a)\right)W^f(z,x_u,a,w)}_{\text{Worker gets good entrepreneurship opportunity}}
\end{aligned}
$$

Adding the value of a match to the firm and to the individual and cancelling terms reveals that the value of the match is independent of w.

D Additional Calibration Details

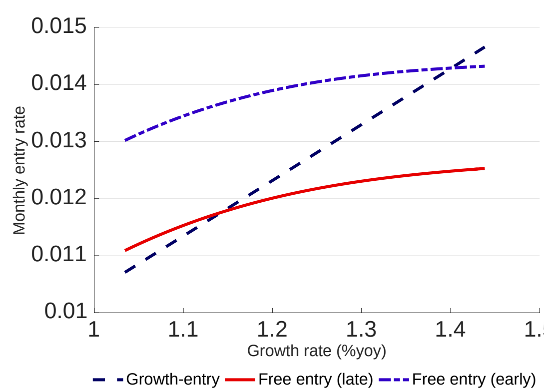
D.1 Solving the model

The model is solved at the monthly frequency. I discretize the grid for productivity using 80 grid points, and I simulate the model for 1,000,000 workers for 1,200 months, discarding the initial 240 months. The high number of workers is necessary to obtain a sufficient number of firms while matching average firm size. A higher number of workers has no meaningful impact on results.

I approximate labor market events assuming that at most one of them can happen in any month, I note that all the finding rates in the model are calibrated to be low (the highest is the monthly job finding rate which is 0.17). In the simulation, I assign workers to firms based on weights corresponding to the number of vacancies it creates relative to the average number of vacancies.

To solve the model, I construct a grid for the growth rate of the economy. For each point on the grid, I guess an allocation, solve individuals' and firms' problem, update the allocation, etc., until the problem has converged for that given growth rate. By aggregating all individuals' entry decisions over the distribution of individuals, I obtain the aggregate entry rate that results from individual optimization for that given growth rate. Subsequently I look for a fixed point such that the given aggregate entry rate is consistent with the guessed growth rate. Figure 23 illustrates the optimal aggregate entry rate as a function of the growth rate, as well as the growth rate that results for a given entry rate. An equilibrium is where the two lines cross.

FIGURE 23. ENTRY RATE AND GROWTH RATE



Under the uniform cost function that I assume, the two lines may cross twice. The lower intersection would be an unstable equilibrium, in the sense that a small deviation would either cause the firm productivity distribution to explode or lead to convergence to the stable equilibrium that I focus on. A different functional form for the cost function that guarantees that the entry rate is sufficiently inelastic at low growth rates may guarantee a unique equilibrium. I do not consider this further, but instead restrict attention to the stable equilibrium.

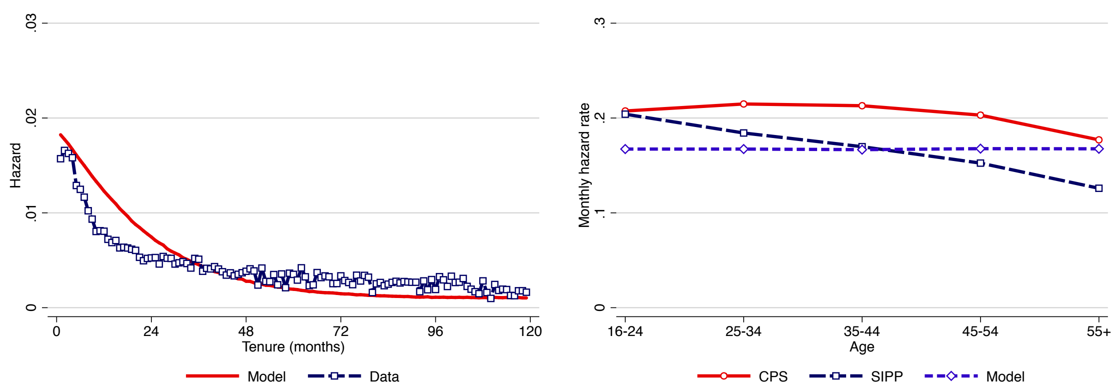
D.2 Worker mobility

The left panel of Figure 24 plots the EU hazard with tenure. The model matches the data well given that neither the magnitude nor the timing of the decline is a target in the calibration. The right panel shows that the model cannot match the modest decline in the UE hazard with age in the data.

FIGURE 24. VALIDATION: EU TENURE PROFILE AND UE LIFE CYCLE PROFILE

(A) EU BY TENURE

(B) UE BY AGE

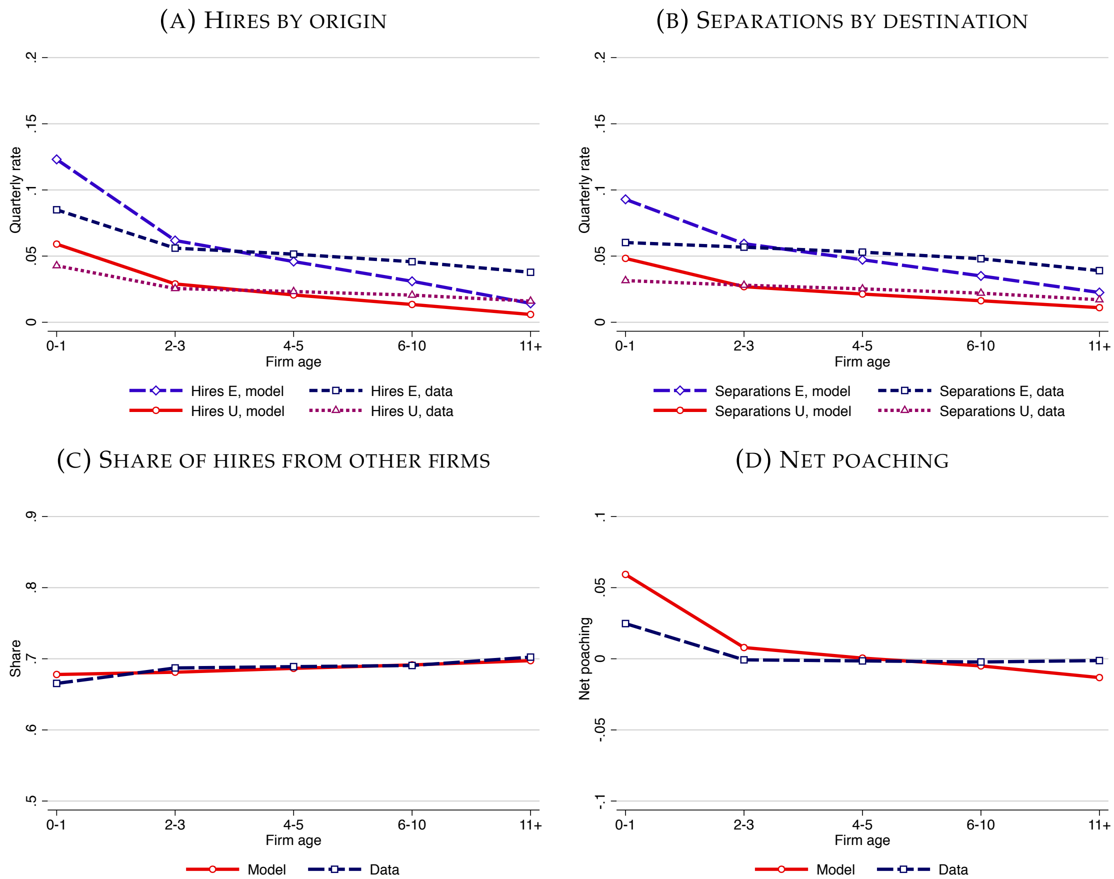


Note: Left: SIPP in 1996–2013; Right: SIPP 2012–2013 adjusted to fit 1985–2007 average and CPS in 2014. Labor force age 16 and older. EU: share of employed in month t who are unemployed in $t+1$; UE: share of unemployed in t who are employed in $t+1$. All are conditional on remaining in the labor force.

D.3 Firm reallocation rates

The top two panels of Figure 25 illustrate that the model captures well empirical hiring and separation patterns with firm age. In particular, young firms have high "churn rates" and in both the model and the data there is a modest increase in the share of hires coming from other firms with firm age. To help visual interpretation, I normalize the level of hires and separation in the model to match the empirical level, but the model also matches well the levels given that worker reallocation in the model is calibrated to match an entirely different data source.

FIGURE 25. VALIDATION: HIRES AND SEPARATIONS BY FIRM AGE

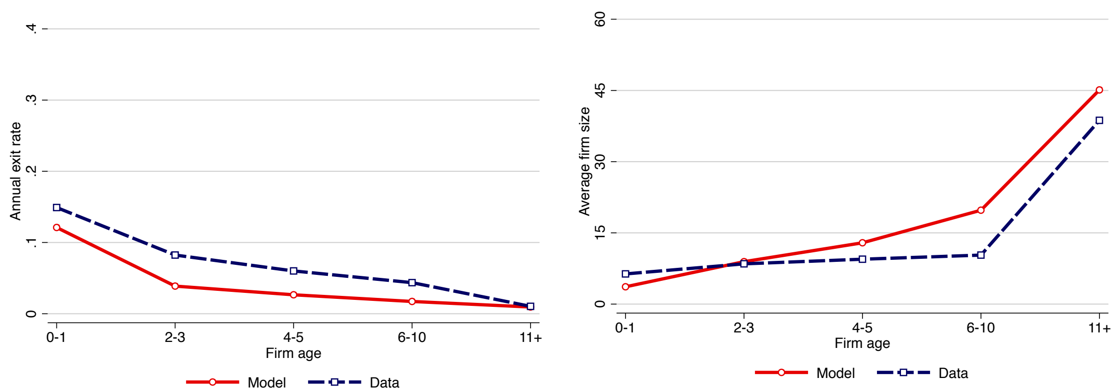


Note: J2J Beta Release in 2014 after HP-filtering the data. Share hires from other firms is the sum of quarterly hires that were employed in the previous quarter divided by the total sum of hires in that firm age group; net poaching is the difference between the sum of hires who were employed in the previous quarter and the sum of separations who are employed in the subsequent quarter in that firm age group divided by the total sum of employment in that firm age group. Hiring and separation rates are normalized to match the corresponding empirical mean.

Figure 26 plots unadjusted exit and firm size by firm age.

FIGURE 26. UNADJUSTED FIRM EXIT AND FIRM SIZE

(A) EXIT RATE (B) AVERAGE FIRM SIZE



Note: BDS in 2014 after HP-filtering the data. Exit rate: sum of employment of firms whose employment in the subsequent year is zero; Firm age: years lapsed since first year with positive employment. All within firm age groups and divided by total employment in that age group.

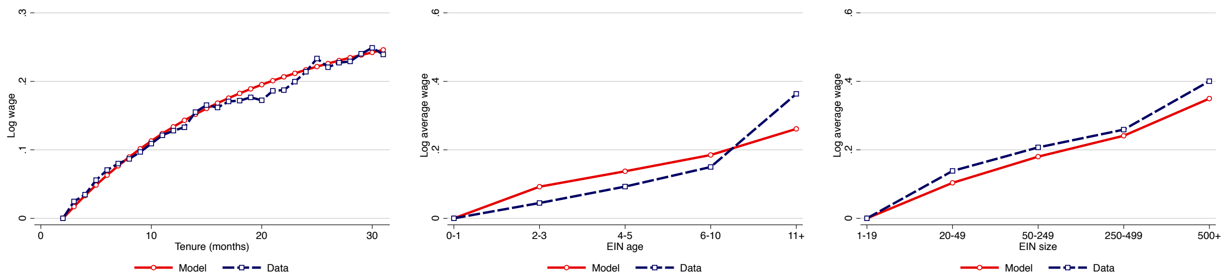
D.4 Wages

Figure 27 shows that the model matches well wages by tenure, firm age and firm size in the data, which serves as a further validation of the structure of the model given that none is targeted.[99] As wage growth with tenure partly results from re-bargaining, the fact that the model fits so well the tenure profile of wages in the left panel supports the pre-set value for workers' bargaining power, β. I show below that the model also matches well empirical gains from JJ mobility, which is also informative about β. Interpreted through the structure of the model, the fact that the model matches well the firm age-pay and firm size-pay gradients indicates that the amount of underlying productivity dispersion in the model is in line with the data.

[99]The model also captures a little over half of life cycle wage growth, with most of the increase taking place early in careers. This is broadly in line with estimates of the contribution of search to life cycle wage growth (**?**).

FIGURE 27. VALIDATION: AVERAGE PAY BY TENURE AND ESTABLISHMENT AGE

(A) TENURE (B) ESTABLISHMENT AGE (C) ESTABLISHMENT SIZE



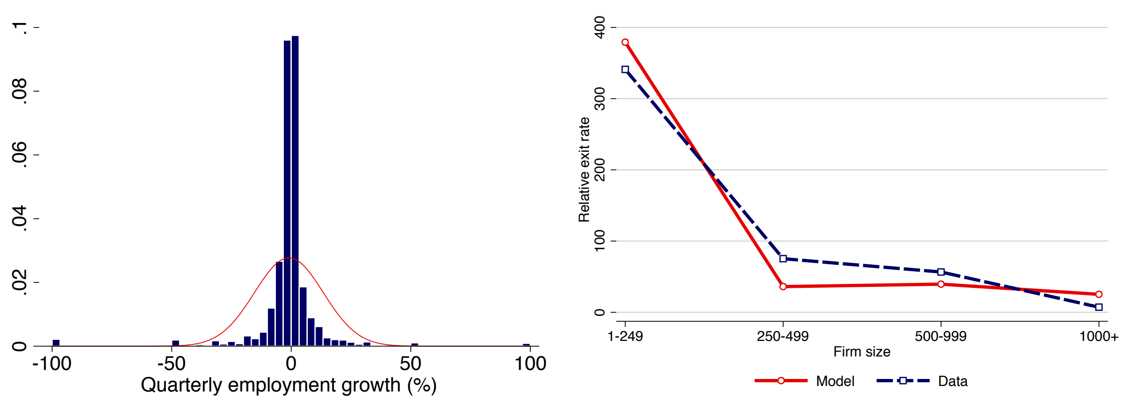
Note: SIPP 1996–2013 (left) and QWI 1993–2014 (middle and right). Left panel: Log real hourly wage at main employer, constructed as total monthly labor income from that employer divided by weeks worked at that employer in the month times average hours per week at that employer. Main employer is the employment spell with the greatest number of hours in the month (splitting on income in case of a tie). Tenure is continuous time since employment spell first started. Right panel: Log average monthly income of workers at Employer Identification Number (EIN).

D.5 Higher order moments and exit by size

Job reallocation can be viewed as the second moment of employment changes at the establishment level. The left panel of Figure 28 shows that the model also replicates well higher order moments of employment changes, specifically the fact that such changes have a large spike at zero and fat tails (Elsby and Michaels, 2013). The right panel of Figure 28 shows that the model matches well the exit rate of firms by firm size in the data.

FIGURE 28. QUARTERLY EMPLOYMENT CHANGES AT FIRM LEVEL AND EXIT RATE BY SIZE

(A) CHANGE IN EMPLOYMENT (B) EXIT



Note: Right: change in employment between t and $t+1$ over employment at t multiplied by 100. Weighted by employment. Right: BDS in 2015 after HP-filtering annual data with smoothing parameter 6.25. Sum of jobs destroyed due to exit of firms from that size group divided by sum of employment in that size group.

D.6 Income inequality and dynamics

Table 18 presents summary statistics on wages in the model and data. As can be seen in the first row, the level of wage inequality is substantially lower than in the data. Several things should be noted with respect to this, though. First, wages are measured without noise in the model, while wage rates in survey data are notoriously noisy. Second, the model features no ex ante heterogeneity in individual ability. A more comparable empirical measure may hence be between-firm dispersion in pay (or AKM firm effects), which typically is estimated to be substantially lower. For instance, Abowd et al. (2002) report a standard deviation of AKM firm effects of 0.231 using hourly wages in the state of Washington based on administrative data for 1984–1993, which is close to the dispersion in wages in the model. As can be seen in the second row, the model matches the dispersion in log average firm pay in the data, constructed as the average annual income of all workers at an establishment. To the extent that this averages out some individual heterogeneity and reduces measurement error by not dividing by hours, this may better align with the model-based moments.

TABLE 13. SUMMARY STATISTICS ON WAGES AND INCOME IN MODEL

Moment	Data source	(1) Data	(2) Model
Standard deviation of wages	AKM firm effect (Abowd et al., 2002)	0.23	0.22
Variance of log average firm pay	Barth et al. (2016)	0.48	0.46
Standard deviation of income innovations	Guvenen et al. (2014)	0.51	0.52
Skewness of income innovations	Guvenen et al. (2014)	-0.31	-0.32
Kurtosis of income innovations			8.71
Pass-through from productivity to wage	Van Reenen (1996)	0.29	0.27
Wage gain from JJ mobility	Topel and Ward (1992)	7%	7%

Note: AKM firm effects based on hourly wages in Washington state 1984–1993; variance of log average firm pay is the variance of log average annual income of an establishment's workers across establishments in 2009; income innovations use total annual log labor income; pass-through coefficient is estimated based on a regression of log wage innovation from December to December on log firm productivity innovation from December to December of workers who remain with the firm between the two years; gain from JJ mobility is monthly wage gain from a JJ move.

The third to fifth row show that the model matches closely the second and third moment of annual income innovations in the data reported by Guvenen et al. (2014) in 2010 based on social security data. The model also displays substantial excess kurtosis, which is in line with other recent findings using social security data from the U.S.[100] The sixth row provides some insight into why the model is able to match income innovations well. The estimated pass-through from annual TFP innovations of the firm to annual wage innovations of workers who remain with the firm between the two years is low, in line with the seminal "rent-sharing" estimate by Van Reenen (1996).[101] Despite random normal shocks hitting firm productivity continuously, the assumption that wages can only be changed by mutual consent implies that only a fraction of productivity innovations is passed on to wages of workers who remain with the firm. Instead, income volatility of workers is much lumpier, driven by labor market shocks including job loss, JJ mobility, and rebargaining of wages in response to more preferable outside offers.[102] This produces a dynamic wage and income process that shares key features with the data, including a spike in annual income changes at zero, negative skewness and excess kurtosis. The final two rows show that the model matches well gains from JJ mobility and the fact that a high share of JJ movers experience wage losses.[103] None of these moments was targeted in the calibration.

[100] Hubmer (2017) develops a one worker-one firm matching model without shocks to firm productivity but with human capital that is subject to a random walk, and reaches a similar conclusion with respect to the ability of a job ladder to match higher order moments of income innovations.

[101] Card et al. (2016) survey the empirical rent-sharing literature and report estimates between 0.05–0.15, i.e. smaller than Van Reenen (1996)'s estimate. Measurement error in the data would give rise to a downward bias of the estimated coefficient.

[102] A similar argument is made in Postel-Vinay and Turon (2010) in a one worker-one firm matching model.

[103] The latter is the result of multiple forces. First, in the discretized model I assume that those who learn that their match productivity is bad may find a new job within the same month. Since these individuals have a bad bargaining position, a relatively high fraction of them experience wage losses when they move. Second, since firm productivity drifts down over time, many workers move to leave a "sinking ship." Since wages are assumed to be fixed until either party may force a renegotiation, many of these workers experience only small wage gains from such mobility.

E Additional Quantitative Results

E.1 Shift in age distribution

Table 14 compares the shift in the age distribution in the model and in the data. As noted in the main text, I target the change in the share of older individuals, which implies that I understate the decline in the share young and overstate the decline in the share middle aged somewhat. Since the young are more mobile than the middle aged and have about the same entrepreneurship entry rates, this will understate the direct impact of aging and presumably also the indirect effect.

TABLE 14. SHARE OF INDIVIDUALS IN EACH AGE GROUP BY PERIOD, MODEL VERSUS DATA

	(1)	(2)	(3)	(4)	(5)	(6)
	Early		Late		Change	
	Data	Model	Data	Model	Data	Model
Young	0.492	0.434	0.356	0.339	-0.136	-0.095
Middle aged	0.231	0.289	0.208	0.226	-0.023	-0.063
Older	0.277	0.277	0.436	0.436	0.159	0.158

Note: Empirical moments corresponds to the share of the labor force age 16–34 (young), 35–44 (middle aged) and 45+ (older) in 1986 and 2015 from the BLS.

E.2 Shifts in firms' job posting decisions

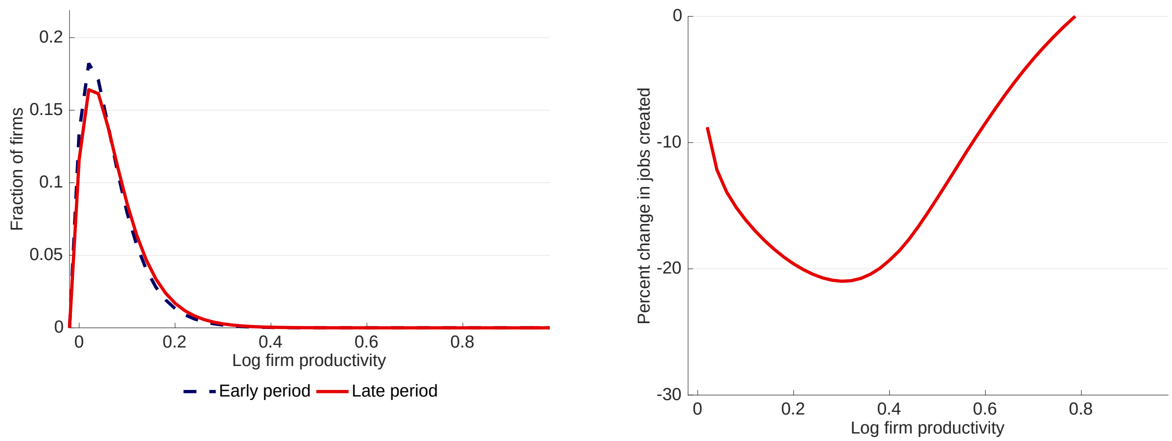
The left panel of Figure 29 plots the underlying distribution of firms in the two periods. I note that the unweighted distribution of firms is substantially to the left of the weighted distribution, as there are many small, unproductive firms in the model. I also note that part of the shift in the employment distribution is driven by a shift in the underlying distribution of firms.[104] The right panel plots the change in vacancies posted by firm productivity between the older and younger economy. As can be seen, firms post more jobs conditional on productivity in the younger economy.

[104] This only explains part of the shift, however, with also a shift of employment across firm ranks.

FIGURE 29. CHANGE IN FIRM PRODUCTIVITY DISTRIBUTION AND JOB CREATION BY PRODUCTIVITY OF THE FIRM

(A) FIRM PRODUCTIVITY DISTRIBUTION

(B) VACANCY CREATION



E.3 Declining variance of shocks versus a fall in the pass-through

Table 15 shows that the model replicates the empirical fact documented by Decker et al. (2017a) that the decline in job reallocation is driven by a weaker pass-through from underlying TFP shocks to employment adjustment.

TABLE 15. PASS-THROUGH FROM PRODUCTIVITY TO EMPLOYMENT INNOVATIONS, MODEL

	(1) All firms	(2) Young firms	(3) Mature firms
Δ TFP	3.504***	5.604***	2.394***
Late period ×Δ TFP	-0.566***	-0.212***	-0.177***

Note: Young firms are <5 years, mature firms $\geq$ 5 years. Outcome variable is annual change in log firm size. Independent variable is annual change in log firm productivity. Weighted by employment.

E.4 Firm aging and the decline in firm dynamics

I compute firm age conditional reallocation rates in a late period, β_a^{late}, and change the employment distribution over firm age assuming that firm age-conditional reallocation rates remain constant,

$$\widehat{\text{Effect of aging}} = \sum_a \beta_a^{\text{late}} \left[\text{share of employment}_a^{\text{early}} - \text{share of employment}_a^{\text{late}} \right] \tag{24}$$

Table 16 shows that the effects of aging in the model match well the reduced-form patterns in the data.[105] As in the data, the shift towards older firms accounts for all (or even more than that) of the decline in exit and a substantial share of the decline in incumbent job reallocation. Firm aging accounts for a relatively larger share in the model due to the more pronounced life cycle profiles of exit and incumbent job reallocation with firm age relative to the data. As noted in the previous section, however, if there is any measurement error in firm age, that would tend to flatten the life cycle profiles and bias the empirical figures towards zero. The model captures the pattern that firm aging accounts for more of the decline in exit than incumbent dynamics.

TABLE 16. FIRM AGING AND FIRM DYNAMICS

	(1)	(2)	(3)	(4)	(5)	(6)
	Early		Late		Change	
	Data	Model	Data	Model	Data	Model
Exit	0.029	0.021	0.020	0.018	-0.008	-0.003
Direct effect	0.029	0.023	0.020	0.018	-0.008	-0.004
% of total					96.8	142.4
Incumbent	0.211	0.176	0.166	0.152	-0.045	-0.024
Direct effect	0.176	0.170	0.166	0.152	-0.010	-0.018
% of total					22.7	74.4

Note: Annual firm reallocation rates. Data moments from the BDS in 1988 and 2014 after HP-filtering the data with smoothing parameter 6.25. Direct effect is based on a shift-share methodology assuming that firm age conditional reallocation rates remain fixed at their late values and only shifting the distribution of firm age. Weighted by employment.

E.5 Direct and indirect effect of aging

Table 17 shows results from a standard shift-share analysis.

[105] For all statistics broken down by firm age, the early period corresponds to 1988 since data on the oldest age group of firms is not available prior to that.

TABLE 17. COMPOSITION VERSUS EQUILIBRIUM EFFECT OF AGING ON WORKER DYNAMICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early		Late		Change		
	Data	Model	Data	Model	Data	Model	Share
EU	0.009	0.006	0.005	0.005	-0.003	-0.001	35.7
Direct effect	0.006	0.005	0.005	0.005	-0.001	-0.000	59.2
% of total					20.7	34.4	
JJ	0.023	0.020	0.018	0.017	-0.005	-0.002	47.6
Direct effect	0.020	0.018	0.018	0.017	-0.002	-0.001	60.2
% of total					40.8	51.7	

Note: Monthly worker reallocation rates from the SIPP in 1986 and 2012–2013. Converted to annual averages and HP-filtered with smoothing parameter 6.25. Direct effect estimated based on a shift-share methodology holding age-conditional mobility rates fixed at the values in the late period and shifting only the age distribution.

E.6 Understanding the decline in dynamism

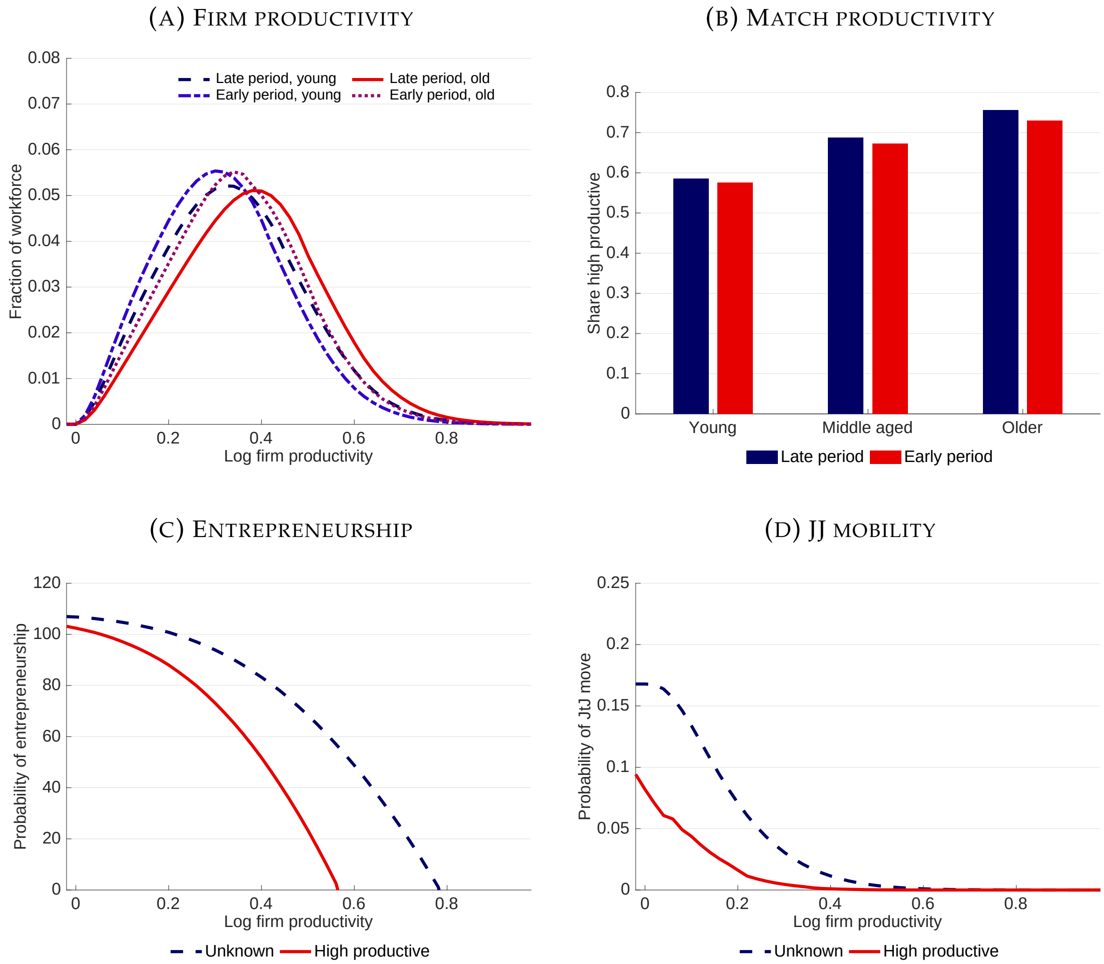
Figure 30 illustrates the equilibrium shifts in the distribution of employment over firm productivity and match productivity from the old to the young economy. The left panel plots the distribution of young and old individuals over firm productivity in the early and late period,[106] while the right panel plots the share of individuals of each age who have learned that they are high-productive in the two periods. The aggregate labor market is shifted to more productive firms in the older economy both because older individuals are on average employed higher up the firm ladder, and because the slower turnover rate of firms endogenously shift the distribution of employment up the firm ladder. Similarly, the share who know that they are in a high productive match is higher in the older economy both because it is higher among older individuals and because the longer employment spells implies that more matches have learned their productivity.

To understand the impact of shifts in the distribution of workers over firm productivity and worker productivity on the probability of entry and making a JJ move, Figure 30 plots the probability of entering entrepreneurship and of accepting an outside job offer as a function of current place in the job ladder and whether the worker knows that he is high-skilled or does not know his skill level.[107] As a worker climbs the job ladder and learns his skill level, he is less likely to enter entrepreneurship and switch employer since it increases his opportunity cost.

[106] Specifically it plots those who have not yet learned their match productivity. To avoid clogging up the graph I do not plot middle aged individuals, but naturally it is in between young and older individuals.

[107] Specifically for middle aged workers in the late period, but the other period and age groups look similar.

FIGURE 30. FIRM AND MATCH PRODUCTIVITY AND ENTRY AND JJ MOBILITY DECISION RULES IN EARLY AND LATE PERIOD

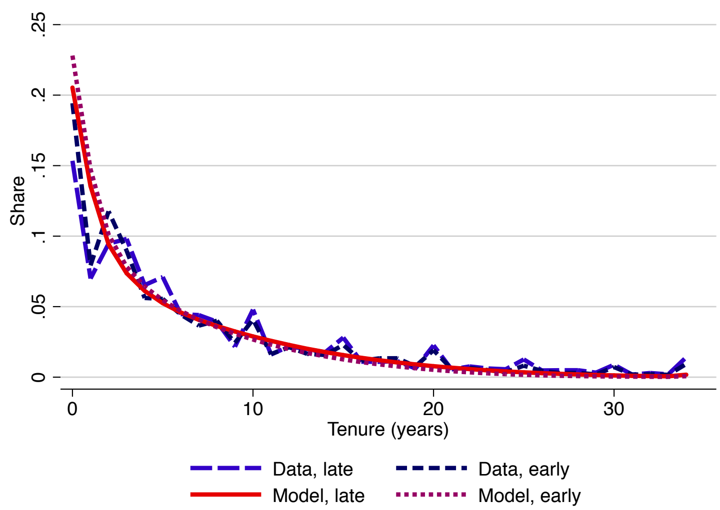


Note: Top left: distribution of young and older individuals over firm productivity (specifically those that have not yet learned their match productivity); Top right: share of individuals who know that they are in a high-productive match, aggregating across all firm productivities; Bottom left: Probability of entering entrepreneurship normalized to 100 for young workers with unknown skill in the late period; Bottom right: Probability of JJ move.

E.7 Tenure distribution in model and data

Figure 31 plots the tenure distribution in the model and the data in the early and late period. The empirical moments are based on the CPS tenure supplements in 1987 and 2014 for workers age 20–64 and was kindly provided to me by Henry Farber. The model matches well the tenure distribution in the CPS in levels, somewhat overpredicting the share of workers at very low tenures. This tentatively supports the lower SIPP based reallocation rates relative to the higher rates in the matched CPS data. Furthermore, the model matches well the change in the tenure distribution over time.

FIGURE 31. TENURE DISTRIBUTION IN MODEL AND DATA, EARLY AND LATE PERIOD



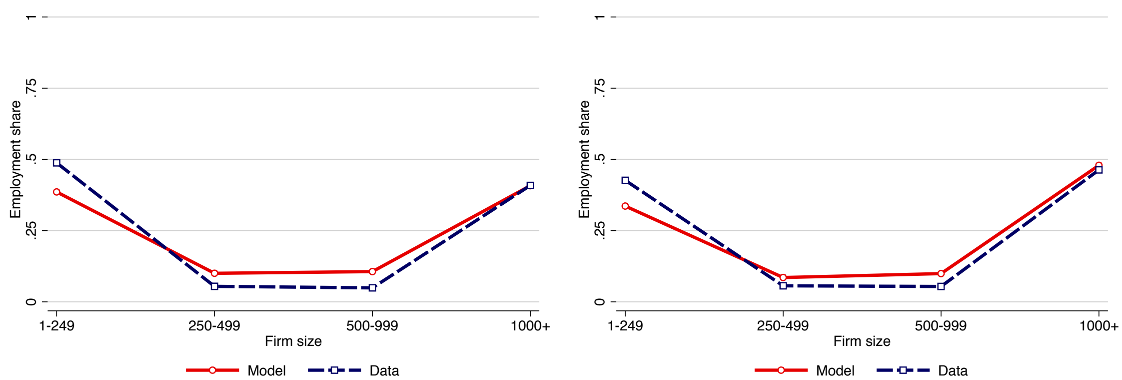
Note: CPS tenure supplements in 1987 and 2014. Workers age 20–64, weighted with provided survey weights. I thank Henry Farber for providing me with these data.

E.8 Shift in employment size distribution

Figure 32 shows that the model captures well changes in the share of employment by firm size over this period, specifically the fact that large firms have seen a modest expansion in their employment share at the expense of small firms.

FIGURE 32. EMPLOYMENT SHARES BY FIRM SIZE IN EARLY AND LATE PERIOD, MODEL AND DATA

(A) EARLY (B) LATE



Note: Data from the BDS in 1986 and 2015 after HP-filtering the annual data with smoothing parameter 6.25.

E.9 Income dynamics

This section evaluates of the effect of aging on income inequality and income dynamics.[108] Panel A offers two main insights on between-firm dispersion in productivity and pay. First, the model matches well the level of between-firm dispersion in pay, despite not targeting this in the calibration. Second, aging increases dispersion in productivity and pay across firms. This is qualitatively in line with the data over this period, although quantitatively it accounts for only a modest share of the increase. Panel B shows the impact of aging on income dynamics, providing three takeaways. First, despite not targeting these moments, the model matches very well the level of both the variance and skewness of annual income innovations in the data.[109] Second, the less dynamic labor market in the older economy is associated with a lower variance of income innovations. The change matches well the trend over this period documented by Guvenen et al. (2014). Third, skewness has become increasingly negative, again in line with empirical trends (Guvenen et al., 2014).[110] Workers are on average further up the ladder in the older economy, with the potential

[108]The model predicts a slight decrease in the labor share from the early to the late period. This highlights that the relevant object for other firms' incentives to create jobs is not the split of payments among existing matches but the productivity of such matches relative to the potential hiring firm. The labor market has become better matched in the sense that individuals are in relatively more productive matches, not in the sense that they are paid more conditional on output.

[109]The model also produces a kurtosis of annual income changes of over 8, in line with recent findings of substantial excess kurtosis in the data. Hubmer (2017) reaches a similar finding in a one worker-firm matching model.

[110]Skewness, however, displays substantial business cycle variation and it is difficult to separate trend from cycle in the data. HP-filtering Guvenen et al. (2014)'s published data from 1978–2010, detrended skewness has declined from

for a greater fall in case of a perverse labor market shock.

TABLE 18. INEQUALITY AND INCOME DYNAMICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early		Late		Change		
	Data	Model	Data	Model	Data	Model	Share
Panel A: Inequality							
Standard deviation of productivity	0.35	0.127	0.42	0.138	0.07	0.011	13.9
Variance of firm pay	0.40	0.446	0.48	0.463	0.08	0.017	21.3
Panel B: Annual income innovations							
Standard deviation	0.545	0.539	0.506	0.515	-0.039	-0.024	61.5
Skewness	-0.213	-0.253	-0.312	-0.323	-0.099	-0.07	70.7

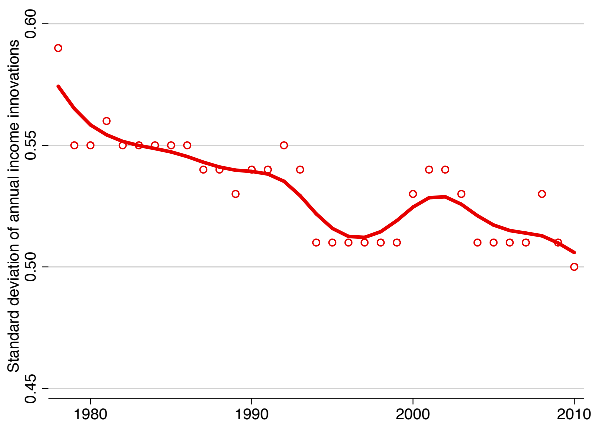
Note: Empirical counterparts are the following: Standard deviation of firm productivity is the standard deviation of within-detailed industry TFP of manufacturing firms from Decker et al. (2017a)'s Figure A1 in HP-filtered data in 1986 and 2011; Standard deviation of wages is the standard deviation of residual log weekly earnings and the variance of firm pay is the variance of log average annual income of all individuals at the firm, both from Barth et al. (2016)'s Figure 1 in 1986 and 2009; Moments of income innovation distribution from Guvenen et al. (2014) in HP-filtered data in 1986 and 2010.

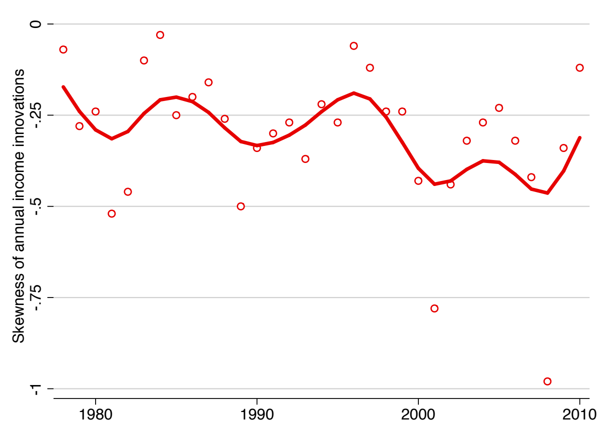
E.10 Empirical trends in income innovations

Figure 33 plots the empirical trend in the standard deviation and skewness of annual income innovations based on the administrative social security data in Guvenen et al. (2014). There is a clear downward trend in income volatility as measured by the standard deviation. Skewness has also declined, although as emphasized by these authors it displays important business cycle variation and hence it is less clear how much to make out of the decline at this point.

-0.213 in 1986 to -0.312 in 2010, while if I instead fit a linear time trend to their raw data skewness is predicted to have fallen secularly from -0.259 in 1986 to -0.404 in 2010. See Appendix E for details.

FIGURE 33. EMPIRICAL TREND IN STANDARD DEVIATION AND SKEWNESS OF ANNUAL LOG INCOME INNOVATIONS





Note: Data from Guvenen et al. (2014). Annual innovations of log income HP-filtered with annual smoothing parameter of 6.25. See their paper for further details.

F Additional Details on Cross-state Regressions

F.1 Construction of data set

Data sources and variable definitions are described in Appendix A. All measures are aggregated to the annual level and HP-filtered with smoothing parameter of 6.25. The BDS covers private sector employment while in the CPS I focus on workers age 19–64. Given that I need one lagged year and one future year of employment to construct growth in GDP per worker at the state level, I focus my regression analysis on the 1978–2014 period.

Although the data identify Washington D.C., I drop D.C. due to the high share of its labor force does not live in the "state." Based on Decennial Census/American Community Survey data from 1980–2015, on average 70 percent of the people that work in D.C. do not live in D.C. (the second highest share is in Delaware with 14 percent). Thus the age composition of people living in D.C. is a poor proxy for the age composition that is important for determining dynamism in the state (results are modestly weaker including D.C.).

F.2 First stage regressions

Table 19 presents first stage regression of the current share of older in the labor force (column 1) or working age population (column 2) on the 10-year lagged share of older workers (with state fixed effects, year effects and growth in state real GDP per worker). Together with state and year effects, the lagged age composition explains 94–95 percent of the overall variation in the current age composition. It explains 27 percent of the residual variation after having taken out state and year effects. The Kleibergen-Paap rk Wald statistic is just over 16.

TABLE 19. FIRST STAGE REGRESSIONS

	(1) LF	(2) WP
10-year lagged share	0.880***	0.860***
	(0.214)	(0.238)
N	1,850	1,850
R2	0.952	0.939
R2 (within)	0.273	0.272

*Note: BDS and CPS 1978–2014. All columns contain state fixed effects, year effects and growth in state real GDP per worker. Dependent variable is share of labor force (column 1) or working age population (column 2) age 19–64 that is age 40–64. Two-way clustered standard errors by state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%. See text for further details.*

F.3 Additional establishment level dynamics

Logs. Table 20 shows the full range of point estimates and their standard errors based on regression (20) with establishment dynamics. All reallocation rates and population shares are in logs.

TABLE 20. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, EMPLOYMENT-WEIGHTED ESTABLISHMENT LEVEL OUTCOMES IN LOGS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
	Baseline		Covar		Sector		Policy	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force								
Job reallocation	-0.448***	-0.527***	-0.386***	-0.476**	-0.354***	-0.440**	-0.430***	-0.527**
	(0.127)	(0.191)	(0.104)	(0.181)	(0.111)	(0.186)	(0.125)	(0.204)
Turnover	-0.630***	-0.961***	-0.558***	-0.919***	-0.503***	-0.861***	-0.593***	-0.945***
	(0.203)	(0.268)	(0.170)	(0.244)	(0.180)	(0.264)	(0.195)	(0.276)
Entry	-0.668***	-0.999***	-0.597***	-0.933***	-0.526***	-0.903***	-0.645***	-1.006***
	(0.189)	(0.247)	(0.158)	(0.236)	(0.159)	(0.247)	(0.193)	(0.263)
Exit	-0.600**	-0.940***	-0.532**	-0.928***	-0.485**	-0.825**	-0.550**	-0.898***
	(0.243)	(0.322)	(0.216)	(0.283)	(0.224)	(0.318)	(0.226)	(0.324)
Panel B: Working age population								
Job reallocation	-0.518***	-0.539***	-0.447***	-0.467**	-0.410***	-0.458**	-0.496***	-0.538**
	(0.124)	(0.186)	(0.105)	(0.195)	(0.114)	(0.186)	(0.123)	(0.197)
Turnover	-0.774***	-0.984***	-0.683***	-0.933***	-0.629***	-0.898***	-0.734***	-0.966***
	(0.202)	(0.256)	(0.163)	(0.256)	(0.184)	(0.263)	(0.194)	(0.259)
Entry	-0.753***	-1.022***	-0.661***	-0.962***	-0.588***	-0.941***	-0.724***	-1.029***
	(0.188)	(0.245)	(0.161)	(0.263)	(0.164)	(0.254)	(0.193)	(0.256)
Exit	-0.809***	-0.962***	-0.729***	-0.934***	-0.682***	-0.860***	-0.759***	-0.918***
	(0.239)	(0.304)	(0.194)	(0.286)	(0.225)	(0.313)	(0.221)	(0.300)

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted establishment dynamics. All columns control for state, year, share female, share college or more, share non-white and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Covariates: controls for the share female, non-white, and with a college degree or more; Sector: controls for share of the labor force in nine aggregate sectors; Policy: controls for state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table 21 summarizes the predicted power of aging on aggregate dynamism across measures from 1986 to 2015. Across all measures and regardless of whether I use the labor force or working age population aging predicts substantial declines.

TABLE 21. PREDICTED CUMULATIVE EFFECT OF AGING ON ESTABLISHMENT REALLOCATION RATES 1986–2015

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Baseline		Covariates		Sector		Policy	
	Raw	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force									
Job	-0.329	-0.144	-0.169	-0.124	-0.153	-0.114	-0.141	-0.138	-0.169
% of raw	100	43.7	51.4	37.7	46.5	34.5	42.9	41.9	51.4
Turnover	-0.477	-0.203	-0.309	-0.179	-0.295	-0.162	-0.277	-0.191	-0.304
% of raw	100	42.5	64.8	37.6	61.9	33.9	58.1	40.0	63.7
Entry	-0.475	-0.215	-0.321	-0.192	-0.300	-0.169	-0.290	-0.207	-0.324
% of raw	100	45.2	67.5	40.4	63.1	35.5	61.0	43.6	68.1
Exit	-0.478	-0.193	-0.302	-0.171	-0.298	-0.156	-0.265	-0.177	-0.289
% of raw	100	40.3	63.2	35.8	62.4	32.6	55.5	36.9	60.4
Panel B: Working age population									
Job	-0.329	-0.135	-0.140	-0.116	-0.122	-0.107	-0.119	-0.129	-0.140
% of raw	100	40.9	42.6	35.3	36.9	32.3	36.2	39.2	42.5
Turnover	-0.477	-0.201	-0.256	-0.178	-0.243	-0.164	-0.233	-0.191	-0.251
% of raw	100	42.2	53.7	37.2	50.9	34.3	49.0	40.1	52.7
Entry	-0.475	-0.196	-0.266	-0.172	-0.25	-0.153	-0.245	-0.188	-0.268
% of raw	100	41.2	55.9	36.1	52.6	32.2	51.5	39.6	56.3
Exit	-0.478	-0.211	-0.250	-0.190	-0.243	-0.177	-0.224	-0.197	-0.239
% of raw	100	44.0	52.3	39.7	50.8	37.1	46.8	41.3	49.9

Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.

Levels. Table 22 shows regression results of establishment dynamics on the share of older workers in levels, while Table 23 summarizes the cumulative predicted impact of aging. The results are more pronounced than in the specification in logs.

TABLE 22. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, EMPLOYMENT-WEIGHTED ESTABLISHMENT LEVEL OUTCOMES IN LEVELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
	Baseline		Covar		Sector		Policy	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force								
Job reallocation	-0.364**	-0.371	-0.386***	-0.415**	-0.283**	-0.288	-0.357**	-0.394*
	(0.141)	(0.229)	(0.108)	(0.181)	(0.110)	(0.174)	(0.136)	(0.231)
Turnover	-0.181**	-0.235*	-0.192***	-0.255**	-0.147**	-0.202**	-0.176**	-0.252*
	(0.080)	(0.131)	(0.063)	(0.100)	(0.063)	(0.097)	(0.076)	(0.130)
Entry	-0.106**	-0.128*	-0.114***	-0.138**	-0.084***	-0.108**	-0.106**	-0.143*
	(0.043)	(0.070)	(0.032)	(0.052)	(0.031)	(0.051)	(0.043)	(0.072)
Exit	-0.075*	-0.106	-0.079**	-0.117**	-0.063*	-0.094*	-0.070*	-0.110*
	(0.040)	(0.064)	(0.035)	(0.052)	(0.034)	(0.050)	(0.037)	(0.062)
Panel B: Working age population								
Job reallocation	-0.409**	-0.379	-0.402***	-0.423**	-0.301**	-0.298	-0.398***	-0.401*
	(0.151)	(0.230)	(0.109)	(0.194)	(0.121)	(0.180)	(0.144)	(0.231)
Turnover	-0.215**	-0.240*	-0.205***	-0.265**	-0.167**	-0.209**	-0.208**	-0.257*
	(0.086)	(0.131)	(0.062)	(0.109)	(0.068)	(0.101)	(0.080)	(0.129)
Entry	-0.116**	-0.131*	-0.110***	-0.145**	-0.085**	-0.112**	-0.115**	-0.145*
	(0.046)	(0.070)	(0.034)	(0.059)	(0.034)	(0.054)	(0.046)	(0.072)
Exit	-0.099**	-0.109*	-0.095***	-0.120**	-0.082**	-0.097*	-0.093**	-0.112*
	(0.042)	(0.064)	(0.032)	(0.054)	(0.036)	(0.052)	(0.038)	(0.061)

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted establishment dynamics. All columns control for state, year, share female, share college or more, share non-white and annual growth in state real GDP per worker. All shares and reallocation rates are in levels. Covariates: controls for the share female, non-white, and with a college degree or more; Sector: controls for share of the labor force in nine aggregate sectors; Policy: controls for state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

TABLE 23. PREDICTED CUMULATIVE EFFECT OF AGING ON ESTABLISHMENT REALLOCATION RATES 1986–2015 BASED ON SPECIFICATION IN LEVELS

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Baseline		Covariates		Sector		Policy	
	Raw	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force									
Job	-0.097	-0.053	-0.054	-0.056	-0.061	-0.041	-0.042	-0.052	-0.057
% of raw	100	54.9	56	58.2	62.5	42.7	43.4	53.8	59.3
Turnover	-0.05	-0.026	-0.034	-0.028	-0.037	-0.021	-0.03	-0.026	-0.037
% of raw	100	52.7	68.2	55.9	74.1	42.8	58.7	51.3	73.3
Entry	-0.028	-0.015	-0.019	-0.017	-0.02	-0.012	-0.016	-0.016	-0.021
% of raw	100	56.1	67.9	60.2	72.9	44.4	57.3	56.2	75.4
Exit	-0.023	-0.011	-0.016	-0.011	-0.017	-0.009	-0.014	-0.01	-0.016
% of raw	100	48.5	68.6	50.7	75.6	40.7	60.5	45.2	70.7
Panel B: Working age population									
Job	-0.097	-0.05	-0.047	-0.05	-0.052	-0.037	-0.037	-0.049	-0.049
% of raw	100	52.1	48.3	51.2	53.8	38.3	38	50.7	51.1
Turnover	-0.05	-0.026	-0.03	-0.025	-0.033	-0.021	-0.026	-0.026	-0.032
% of raw	100	52.7	58.9	50.4	65	40.9	51.4	51.1	63.1
Entry	-0.028	-0.014	-0.016	-0.014	-0.018	-0.01	-0.014	-0.014	-0.018
% of raw	100	51.8	58.6	49.2	64.5	37.8	50.1	51.3	64.9
Exit	-0.023	-0.012	-0.013	-0.012	-0.015	-0.01	-0.012	-0.012	-0.014
% of raw	100	53.8	59.3	51.7	65.5	44.6	52.9	50.9	60.8

Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.

Instrumenting with the total number of people age 40–64. Table 24 compares point estimates and their standard errors in the baseline OLS specification in column 1 and IV specification in column 2 with an IV specification that instruments for the current share of older workers using the (log) total number of people age 40–64 in year t who were born state s, regardless of where they currently reside. I construct this based on information in Decennial Censi in 1970, 1980, 1990 and 2000 as well as the American Community Survey in 2001–2014 on where a person was born (I linearly interpolate between Census years in the early years). The idea is that to the extent that mobility is imperfect, if relatively more people were born in state s 40–64 years ago (conditional on state and year effects) this should be reflected in a higher share of older people currently.[111] Although Table 24 indicates that even larger estimates obtain when I use this instrument, standard errors are substantially larger. Furthermore, the i.i.d. assumption on errors is inapplicable and the Kleibergen-Paap Wald statistic suggest that the instrument is weak with a value just over four.

[111]Note that this is not equivalent to the number of people born in the state. It is possible that mortality rates covary with business dynamics. I have not been able to acquire birth rates by state back to 1914.

Hence I do not read much into these results, but focus on my 10-year lagged instrument.

TABLE 24. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, EMPLOYMENT-WEIGHTED ESTABLISHMENT DYNAMICS WITH ALTERNATIVE INSTRUMENT

	(1)	(2)	(3)
	OLS	Lagged share	Number born
Panel A: Labor force			
Job reallocation	-0.448***	-0.527***	-1.127**
	(0.126)	(0.191)	(0.466)
Establishment turnover	-0.630***	-0.961***	-1.645**
	(0.199)	(0.268)	(0.737)
Entry rate	-0.668***	-0.999***	-1.721***
	(0.200)	(0.247)	(0.594)
Exit rate	-0.600**	-0.940***	-1.484
	(0.227)	(0.322)	(1.043)
Panel B: Working age population			
Job reallocation	-0.518***	-0.539***	-0.988***
	(0.119)	(0.186)	(0.333)
Establishment turnover	-0.774***	-0.984***	-1.442***
	(0.196)	(0.256)	(0.526)
Entry rate	-0.753***	-1.022***	-1.508***
	(0.196)	(0.245)	(0.459)
Exit rate	-0.809***	-0.962***	-1.300
	(0.220)	(0.304)	(0.781)

*Note: BDS, CPS, Intercensal Censi, Decennial Censi and ACS 1970–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted establishment dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Lagged share: instrumenting for current share of older using 10-year lagged share in that age group; Number born: instrumenting for current share of older using log number of people born in state 40–64 years earlier (who are currently alive). Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

F.4 Firm dynamics

Logs. Table 25 shows point estimates and their standard errors based on regression (20) with firm level outcomes in logs. Table 26 shows the cumulative predicted impact of aging between 1986 and 2015 based on these specifications. The predicted impact of aging is if anything even larger when using firm-level outcomes.

TABLE 25. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, EMPLOYMENT-WEIGHTED FIRM LEVEL OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline		Covariates		Sector		Policy	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force								
Turnover	-0.764***	-1.266***	-0.685***	-1.237***	-0.608***	-1.142***	-0.743***	-1.321***
	(0.230)	(0.302)	(0.199)	(0.293)	(0.201)	(0.285)	(0.224)	(0.301)
Entry	-0.827***	-1.361***	-0.748***	-1.316***	-0.647***	-1.249***	-0.814***	-1.425***
	(0.199)	(0.278)	(0.174)	(0.287)	(0.173)	(0.264)	(0.201)	(0.283)
Exit	-0.712**	-1.203***	-0.636**	-1.191***	-0.567**	-1.044***	-0.659**	-1.222***
	(0.298)	(0.355)	(0.285)	(0.333)	(0.274)	(0.348)	(0.294)	(0.349)
Panel B: Working age population								
Turnover	-0.923***	-1.296***	-0.814***	-1.254***	-0.744***	-1.190***	-0.895***	-1.350***
	(0.223)	(0.299)	(0.179)	(0.312)	(0.203)	(0.291)	(0.212)	(0.290)
Entry	-0.932***	-1.393***	-0.831***	-1.353***	-0.730***	-1.302***	-0.907***	-1.456***
	(0.195)	(0.291)	(0.165)	(0.316)	(0.177)	(0.282)	(0.194)	(0.285)
Exit	-0.921***	-1.231***	-0.825***	-1.202***	-0.753***	-1.088***	-0.869***	-1.249***
	(0.283)	(0.339)	(0.249)	(0.344)	(0.270)	(0.343)	(0.273)	(0.326)

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted firm dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Covariates: additionally controls for the share female, share college or more, share non-white (in logs); Sector: additionally controls for covariates and the share of the labor force in nine aggregate sectors; Policy: additionally controls for covariates and state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

TABLE 26. PREDICTED CUMULATIVE EFFECT OF AGING ON FIRM REALLOCATION RATES 1986–2015

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Baseline		Covariates		Sector		Policy	
	Raw	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force									
Turnover	-0.486	-0.246	-0.407	-0.220	-0.398	-0.195	-0.367	-0.239	-0.425
% of total	100	50.5	83.7	45.3	81.7	40.2	75.5	49.1	87.3
Entry	-0.627	-0.266	-0.437	-0.241	-0.423	-0.208	-0.402	-0.262	-0.458
% of total	100	42.4	69.8	38.4	67.5	33.2	64.1	41.7	73
Exit	-0.325	-0.229	-0.387	-0.205	-0.383	-0.182	-0.336	-0.212	-0.393
% of total	100	70.4	118.9	62.9	117.8	56.0	103.2	65.2	120.8
Panel B: Working age population									
Turnover	-0.486	-0.24	-0.337	-0.212	-0.326	-0.194	-0.309	-0.233	-0.351
% of total	100	49.4	69.3	43.5	67.0	39.8	63.6	47.9	72.2
Entry	-0.627	-0.242	-0.362	-0.216	-0.352	-0.19	-0.339	-0.236	-0.379
% of total	100	38.7	57.8	34.5	56.1	30.3	54	37.6	60.4
Exit	-0.325	-0.239	-0.32	-0.215	-0.313	-0.196	-0.283	-0.226	-0.325
% of total	100	73.6	98.5	66.0	96.1	60.3	87.1	69.5	99.9

Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend.

Levels. Table 27 shows estimated point estimates and their standard errors from regressions with firm-level measures of dynamics in levels. Table 28 shows the predicted cumulative effect of aging on firm dynamics based on the specification in levels.

TABLE 27. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, EMPLOYMENT-WEIGHTED FIRM LEVEL OUTCOMES IN LEVELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline		Covariates		Sector		Policy	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force								
Turnover	-0.120**	-0.169**	-0.122***	-0.179***	-0.097***	-0.151***	-0.122***	-0.188**
	(0.045)	(0.072)	(0.035)	(0.054)	(0.035)	(0.052)	(0.043)	(0.071)
Entry	-0.079***	-0.104**	-0.080***	-0.108***	-0.061***	-0.091***	-0.082***	-0.117**
	(0.026)	(0.043)	(0.018)	(0.030)	(0.019)	(0.030)	(0.026)	(0.044)
Exit	-0.042*	-0.067**	-0.043**	-0.072***	-0.037*	-0.061**	-0.040*	-0.070**
	(0.022)	(0.032)	(0.020)	(0.026)	(0.019)	(0.025)	(0.022)	(0.030)
Panel B: Working age population								
Turnover	-0.140***	-0.173**	-0.128***	-0.184***	-0.107***	-0.156***	-0.140***	-0.191**
	(0.048)	(0.072)	(0.032)	(0.059)	(0.038)	(0.054)	(0.044)	(0.070)
Entry	-0.087***	-0.106**	-0.078***	-0.112***	-0.063***	-0.094***	-0.089***	-0.120**
	(0.027)	(0.043)	(0.018)	(0.035)	(0.020)	(0.032)	(0.027)	(0.044)
Exit	-0.054**	-0.068**	-0.050***	-0.073***	-0.045**	-0.063**	-0.051**	-0.072**
	(0.022)	(0.032)	(0.017)	(0.027)	(0.019)	(0.026)	(0.021)	(0.030)

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted firm dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in levels. Covariates: additionally controls for the share female, share college or more, share non-white (in logs); Sector: additionally controls for covariates and the share of the labor force in nine aggregate sectors; Policy: additionally controls for covariates and state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

TABLE 28. PREDICTED CUMULATIVE EFFECT OF AGING ON FIRM REALLOCATION RATES IN LEVELS 1986–2015

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Baseline		Covariates		Sector		Policy	
	Raw	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force									
Turnover	-0.025	-0.018	-0.025	-0.018	-0.026	-0.014	-0.022	-0.018	-0.027
% of raw	100	69.8	98.2	70.6	103.8	56.5	87.4	70.6	108.8
Entry	-0.017	-0.011	-0.015	-0.012	-0.016	-0.009	-0.013	-0.012	-0.017
% of raw	100	66.1	87	67.1	90.4	51.2	76.4	68.6	98.4
Exit	-0.008	-0.006	-0.01	-0.006	-0.011	-0.005	-0.009	-0.006	-0.01
% of raw	100	79.7	125	80	135.6	69.4	114.1	74.7	131.8
Panel B: Working age population									
Turnover	-0.025	-0.017	-0.021	-0.016	-0.023	-0.013	-0.019	-0.017	-0.024
% of raw	100	68.8	84.8	62.7	90.3	52.7	76.5	68.7	93.7
Entry	-0.017	-0.011	-0.013	-0.01	-0.014	-0.008	-0.012	-0.011	-0.015
% of raw	100	61.7	75.1	55.6	79.6	44.5	66.8	63	84.7
Exit	-0.008	-0.007	-0.008	-0.006	-0.009	-0.006	-0.008	-0.006	-0.009
% of raw	100	85.8	107.9	79.5	115.6	71.8	99.8	81.3	113.5

Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.

F.5 Labor supply growth

Table 29 presents point estimates and standard errors from a joint regression framework with establishment and firm level reallocation rates on the share of older workers and growth in labor supply. Labor supply growth is positively related to establishment and firm entry, in line with findings in Karahan et al. (2016). The point estimate is strongly statistically significant. The relationship with establishment and firm turnover is economically and statistically weaker, due to a negative correlation with the exit rate. Across the board, controlling for labor supply growth has very little impact on the estimated coefficient on the share of older in the labor force/working age population.

Table 30 summarizes the cumulative predicted power of changes in the age composition and labor supply growth on establishment and firm dynamics from 1986 to 2015. In all fairness, it should be noted that a big share of the decline in labor supply growth happened in the late 1970s and early 1980s, which this calculation misses. Going back to 1978 raises the predicted decline due to weaker labor supply growth by a couple of percentage points.

TABLE 29. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, EMPLOYMENT-WEIGHTED ESTABLISHMENT LEVEL OUTCOMES IN LEVELS

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Labor force				Working age population			
		OLS		IV		OLS		IV	
		Base	LF	Base	LF	Base	LF	Base	LF
Panel A: Establishment dynamics									
JR	Age	-0.448***	-0.439***	-0.527***	-0.534***	-0.518***	-0.503***	-0.539***	-0.553***
		(0.127)	(0.123)	(0.191)	(0.186)	(0.124)	(0.118)	(0.186)	(0.176)
	Δ		0.435**		0.411**		0.668***		0.649***
			(0.162)		(0.154)		(0.203)		(0.191)
Turnover	Age	-0.630***	-0.622***	-0.961***	-0.966***	-0.774***	-0.760***	-0.984***	-0.995***
		(0.203)	(0.200)	(0.268)	(0.264)	(0.202)	(0.197)	(0.256)	(0.246)
	Δ		0.387		0.302		0.630**		0.543*
			(0.230)		(0.226)		(0.290)		(0.276)
Entry	Age	-0.668***	-0.641***	-0.999***	-1.018***	-0.753***	-0.716***	-1.022***	-1.053***
		(0.189)	(0.180)	(0.247)	(0.228)	(0.188)	(0.177)	(0.245)	(0.220)
	Δ		1.278***		1.185***		1.590***		1.467***
			(0.406)		(0.381)		(0.545)		(0.503)
Exit	Age	-0.600**	-0.615**	-0.940***	-0.927***	-0.809***	-0.823***	-0.962***	-0.948***
		(0.243)	(0.245)	(0.322)	(0.329)	(0.239)	(0.243)	(0.304)	(0.312)
	Δ		-0.699*		-0.776*		-0.583		-0.629
			(0.378)		(0.402)		(0.389)		(0.404)
Panel B: Firm dynamics									
Turnover	Age	-0.764***	-0.760***	-1.266***	-1.268***	-0.923***	-0.908***	-1.296***	-1.307***
		(0.230)	(0.227)	(0.302)	(0.301)	(0.223)	(0.216)	(0.299)	(0.291)
	Δ		0.209		0.084		0.656**		0.510*
			(0.250)		(0.248)		(0.296)		(0.296)
Entry	Age	-0.827***	-0.801***	-1.361***	-1.379***	-0.932***	-0.896***	-1.393***	-1.423***
		(0.199)	(0.188)	(0.278)	(0.264)	(0.195)	(0.179)	(0.291)	(0.275)
	Δ		1.219***		1.078***		1.617***		1.424***
			(0.414)		(0.384)		(0.559)		(0.519)
Exit	Age	-0.712**	-0.732**	-1.203***	-1.184***	-0.921***	-0.932***	-1.231***	-1.218***
		(0.298)	(0.301)	(0.355)	(0.365)	(0.283)	(0.288)	(0.339)	(0.344)
	Δ		-0.984*		-1.095*		-0.499		-0.604
			(0.509)		(0.542)		(0.521)		(0.555)

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older ("Age"), and annual log difference in labor force participants/working age population age 19–64 ("Δ") on employment-weighted establishment dynamics. All columns control for state fixed effects, year effects, and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

TABLE 30. PREDICTED CUMULATIVE EFFECT OF AGING ON ESTABLISHMENT AND FIRM REALLOCATION RATES DUE TO AGING AND LABOR SUPPLY GROWTH, 1986–2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		OLS			IV		
	Raw	Base	Age	Δ	Base	Age	Δ
Panel A: Establishment dynamics with labor force							
Job reallocation	-0.329	-0.144	-0.141	-0.007	-0.169	-0.172	-0.006
% of raw	100	44	43	2	51	52	2
Turnover	-0.477	-0.203	-0.2	-0.006	-0.309	-0.311	-0.005
% of raw	100	43	42	1	65	65	1
Entry	-0.475	-0.215	-0.206	-0.02	-0.321	-0.327	-0.018
% of raw	100	45	43	4	68	69	4
Exit	-0.478	-0.193	-0.198	0.011	-0.302	-0.298	0.012
% of raw	100	40	41	-2	63	62	-2
Panel B: Firm dynamics with labor force							
Turnover	-0.486	-0.246	-0.244	-0.003	-0.407	-0.408	-0.001
% of raw	100	51	50	1	84	84	0
Entry	-0.627	-0.266	-0.258	-0.019	-0.437	-0.443	-0.016
% of raw	100	42	41	3	70	71	3
Exit	-0.325	-0.229	-0.235	0.015	-0.387	-0.381	0.017
% of raw	100	70	72	-5	119	117	-5
Panel C: Establishment dynamics with working age population							
Job reallocation	-0.329	-0.135	-0.131	-0.004	-0.14	-0.144	-0.004
% of raw	100	41	40	1	43	44	1
Turnover	-0.477	-0.201	-0.198	-0.004	-0.256	-0.259	-0.003
% of raw	100	42	41	1	54	54	1
Entry	-0.475	-0.196	-0.186	-0.009	-0.266	-0.274	-0.008
% of raw	100	41	39	2	56	58	2
Exit	-0.478	-0.211	-0.214	0.003	-0.25	-0.247	0.004
% of raw	100	44	45	-1	52	52	-1
Panel D: Firm dynamics with working age population							
Turnover	-0.486	-0.24	-0.236	-0.004	-0.337	-0.34	-0.003
% of raw	100	49	49	1	69	70	1
Entry	-0.627	-0.242	-0.233	-0.009	-0.362	-0.37	-0.008
% of raw	100	39	37	1	58	59	1
Exit	-0.325	-0.239	-0.242	0.003	-0.32	-0.317	0.003
% of raw	100	74	75	-1	98	97	-1

Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend.

F.6 Unweighted dynamics

Table 31 shows the estimated impact of aging on unweighted establishment and firm dynamics. Table 32 summarizes the predicted cumulative declines based on these regressions. Aging predicts an even larger share of the declines than in the employment-weighted measures.

TABLE 31. ESTIMATED COEFFICIENT ON SHARE OF LABOR FORCE/POPULATION THAT IS AGE 40 AND OLDER, UNWEIGHTED ESTABLISHMENT AND FIRM LEVEL OUTCOMES IN LOGS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline		Covariates		Sector		Policy	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Establishment dynamics with labor force								
Turnover	-0.111***	-0.204***	-0.108***	-0.213***	-0.089***	-0.189***	-0.114***	-0.217***
	(0.038)	(0.051)	(0.033)	(0.045)	(0.033)	(0.043)	(0.038)	(0.052)
Entry	-0.069***	-0.122***	-0.068***	-0.126***	-0.059***	-0.121***	-0.073***	-0.135***
	(0.023)	(0.030)	(0.022)	(0.028)	(0.019)	(0.024)	(0.025)	(0.032)
Exit	-0.043**	-0.082***	-0.041***	-0.087***	-0.030*	-0.068***	-0.041***	-0.082***
	(0.017)	(0.026)	(0.013)	(0.021)	(0.015)	(0.024)	(0.015)	(0.025)
Panel B: Firm dynamics with labor force								
Turnover	-0.113***	-0.202***	-0.110***	-0.207***	-0.094***	-0.192***	-0.115***	-0.216***
	(0.032)	(0.037)	(0.029)	(0.036)	(0.030)	(0.033)	(0.032)	(0.038)
Entry	-0.074***	-0.127***	-0.073***	-0.130***	-0.064***	-0.126***	-0.079***	-0.142***
	(0.020)	(0.027)	(0.018)	(0.027)	(0.017)	(0.022)	(0.022)	(0.028)
Exit	-0.039***	-0.075***	-0.036***	-0.077***	-0.030**	-0.066***	-0.035***	-0.074***
	(0.013)	(0.016)	(0.013)	(0.016)	(0.014)	(0.018)	(0.012)	(0.017)
Panel C: Establishment dynamics with working age population								
Turnover	-0.130***	-0.208***	-0.115***	-0.214***	-0.105***	-0.197***	-0.132***	-0.222***
	(0.040)	(0.048)	(0.032)	(0.046)	(0.034)	(0.042)	(0.039)	(0.047)
Entry	-0.074***	-0.125***	-0.064***	-0.126***	-0.064***	-0.126***	-0.077***	-0.138***
	(0.025)	(0.029)	(0.022)	(0.030)	(0.020)	(0.025)	(0.027)	(0.030)
Exit	-0.056***	-0.084***	-0.050***	-0.088***	-0.041***	-0.071***	-0.055***	-0.084***
	(0.016)	(0.024)	(0.012)	(0.021)	(0.015)	(0.024)	(0.014)	(0.024)
Panel D: Firm dynamics with working age population								
Turnover	-0.127***	-0.206***	-0.112***	-0.208***	-0.107***	-0.200***	-0.129***	-0.221***
	(0.033)	(0.035)	(0.028)	(0.038)	(0.031)	(0.032)	(0.033)	(0.034)
Entry	-0.078***	-0.130***	-0.069***	-0.131***	-0.068***	-0.131***	-0.084***	-0.145***
	(0.022)	(0.027)	(0.018)	(0.029)	(0.018)	(0.024)	(0.023)	(0.027)
Exit	-0.048***	-0.077***	-0.043***	-0.078***	-0.039***	-0.069***	-0.045***	-0.076***
	(0.012)	(0.015)	(0.010)	(0.017)	(0.013)	(0.017)	(0.011)	(0.015)

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on unweighted establishment and firm dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Covariates: additionally controls for the share female, share college or more, share non-white (in logs); Sector: additionally controls for covariates and the share of the labor force in nine aggregate sectors; Policy: additionally controls for covariates and state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

TABLE 32. PREDICTED CUMULATIVE EFFECT OF AGING ON ESTABLISHMENT AND FIRM UNWEIGHTED REALLOCATION RATES IN LOGS 1986–2015

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Baseline		Covariates		Sector		Policy	
	Raw	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Establishment dynamics with labor force									
Turnover	-0.07	-0.036	-0.065	-0.035	-0.068	-0.029	-0.061	-0.037	-0.07
% of raw	100	51.4	93.9	50	98.2	40.9	87	52.4	99.9
Entry	-0.042	-0.022	-0.039	-0.022	-0.04	-0.019	-0.039	-0.023	-0.043
% of raw	100	53.1	94.3	52.5	97.4	45.8	93.2	56.1	104.1
Exit	-0.028	-0.014	-0.026	-0.013	-0.028	-0.009	-0.022	-0.013	-0.026
% of raw	100	48.8	93.3	46.4	99.4	33.7	77.8	47	93.8
Panel B: Firm dynamics with labor force									
Turnover	-0.059	-0.036	-0.065	-0.035	-0.067	-0.03	-0.062	-0.037	-0.07
% of raw	100	62	110.2	59.9	113.2	51.6	104.7	62.8	118.1
Entry	-0.045	-0.024	-0.041	-0.024	-0.042	-0.021	-0.04	-0.026	-0.046
% of raw	100	52.9	90.2	52	92.5	45.5	89.4	56.5	101.1
Exit	-0.014	-0.013	-0.024	-0.012	-0.025	-0.01	-0.021	-0.011	-0.024
% of raw	100	91.7	177	85.5	182.2	71.4	155.8	83.3	174.4
Panel C: Establishment dynamics with working age population									
Turnover	-0.07	-0.034	-0.054	-0.03	-0.056	-0.027	-0.051	-0.034	-0.058
% of raw	100	48.4	77.7	42.7	80	39.1	73.4	49.1	82.6
Entry	-0.042	-0.019	-0.032	-0.017	-0.033	-0.017	-0.033	-0.02	-0.036
% of raw	100	46	78.1	40.2	79.1	39.8	78.6	48.1	86.1
Exit	-0.028	-0.015	-0.022	-0.013	-0.023	-0.011	-0.018	-0.014	-0.022
% of raw	100	51.8	77.2	46.5	81.5	38	65.6	50.6	77.5
Panel D: Firm dynamics with working age population									
Turnover (firms)	-0.059	-0.033	-0.054	-0.029	-0.054	-0.028	-0.052	-0.033	-0.057
% of raw	100	56	91.2	49.6	92	47.5	88.3	56.9	97.7
Entry (firms)	-0.045	-0.02	-0.034	-0.018	-0.034	-0.018	-0.034	-0.022	-0.038
% of raw	100	45.1	74.7	39.8	75.3	39.3	75.4	48.3	83.6
Exit (firms)	-0.014	-0.013	-0.02	-0.011	-0.02	-0.01	-0.018	-0.012	-0.02
% of raw	100	92.1	146.5	81.9	148.1	74.5	131.4	85.3	144.2

Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.

F.7 Additional worker dynamics

Table 33 shows the estimated coefficient and standard error on the share older in the state as well as the estimated age coefficients and their standard errors based on the specification with worker reallocation rates.

TABLE 33. WORKER DYNAMICS

	(1)	(2)	(3)	(4)	(5)	(6)
	EU		JJ		UE	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force						
Share of older in state	-0.445***	-0.915**	-0.501**	-0.112	-0.084	-0.228
	(0.142)	(0.373)	(0.226)	(0.728)	(0.124)	(0.271)
Direct effects						
19–24	0.742***	0.742***	0.801***	0.801***	0.071***	0.071***
	(0.029)	(0.029)	(0.024)	(0.024)	(0.017)	(0.017)
25–34	0.087**	0.088**	0.213***	0.213***	0.013	0.013
	(0.034)	(0.034)	(0.020)	(0.020)	(0.016)	(0.016)
35–44	-0.135***	-0.135***	-0.035	-0.035	-0.003	-0.003
	(0.034)	(0.034)	(0.027)	(0.027)	(0.013)	(0.013)
45–54	-0.168***	-0.168***	-0.129***	-0.128***	-0.012	-0.012
	(0.023)	(0.023)	(0.022)	(0.022)	(0.012)	(0.012)
Panel B: Working age population						
Share of older in state	-0.491***	-0.931**	-0.642***	-0.127	-0.015	-0.232
	(0.158)	(0.404)	(0.215)	(0.824)	(0.122)	(0.278)
Direct effects						
19–24	0.742***	0.742***	0.801***	0.801***	0.071***	0.071***
	(0.029)	(0.029)	(0.024)	(0.024)	(0.017)	(0.017)
25–34	0.087**	0.088**	0.213***	0.213***	0.013	0.013
	(0.034)	(0.034)	(0.020)	(0.020)	(0.016)	(0.016)
35–44	-0.135***	-0.135***	-0.035	-0.035	-0.003	-0.003
	(0.034)	(0.034)	(0.027)	(0.027)	(0.013)	(0.013)
45–54	-0.168***	-0.168***	-0.129***	-0.128***	-0.012	-0.012
	(0.023)	(0.023)	(0.022)	(0.022)	(0.012)	(0.012)

Note: CPS 1994–2014 (JJ) and 1978–2014 (EU/UE). All columns control for state fixed effects, age fixed effects, year effects and annual growth in state real GDP per worker. Share of older is the log share of the labor force/population age 19–64 that is age 40–64. The dependent variables are the log of HP-filtered annualized monthly worker reallocation rates. Two-way clustered standard errors at state and year level.

Table 34 compares the predicted direct and indirect effect of aging on worker dynamics over this period with the raw log declines in the SIPP and the CPS over this period.[112] A conservative reading of the evidence suggests that aging may account for 30 percent of the decline in JJ mobility, 40 percent of the fall in EU mobility and not much of the recent decline in UE mobility.

[112] The predicted direct effect of aging on JJ and EU mobility is somewhat smaller than the decomposition in Section 2 due to a less pronounced life-cycle of these hazard rates in the CPS relative to the SIPP.

TABLE 34. CUMULATIVE PREDICTED EFFECT OF AGING ON WORKER MOBILITY, 1986–2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Indirect effect			
	Raw data			Labor force		Working age pop.	
	SIPP	CPS	Direct effect	OLS	IV	OLS	IV
JJ	-0.365	-0.401	-0.069	-0.161	-0.036	-0.166	-0.033
% of SIPP	100	109.7	18.8	44.0	9.8	45.5	9.0
EU	-0.472	-0.290	-0.055	-0.143	-0.293	-0.127	-0.241
% of SIPP	100	61.5	11.7	30.2	62.1	26.9	51.1
UE	-0.675	-0.120	-0.006	-0.027	-0.073	-0.004	-0.06
% of SIPP	100	17.8	0.80	4.0	10.8	0.6	8.9

Note: CPS 1978–2014, SIPP 1985–2013 and Intercensal Censi 1969–2014. Cumulative predicted effect of aging from 1986 to 2015 in logs (starting in 1994 for JJ in the CPS).

Labor supply. Table 35 shows estimates of different worker reallocation rates on the age composition controlling for labor supply growth.

TABLE 35. WORKER DYNAMICS WITH LABOR SUPPLY GROWTH

	(1)	(2)	(3)	(4)	(5)	(6)
	EU		JJ		UE	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Labor force						
Share of older in state	-0.484***	-0.898**	-0.502**	0.095	-0.059	-0.248
	(0.153)	(0.365)	(0.229)	(0.689)	(0.126)	(0.271)
Annual growth in supply	-1.954***	-2.058***	-0.983	-0.982	1.545***	1.501***
	(0.595)	(0.624)	(0.739)	(0.791)	(0.479)	(0.463)
Direct effects						
19–24	0.742***	0.742***	0.801***	0.801***	0.070***	0.070***
	(0.029)	(0.029)	(0.024)	(0.024)	(0.017)	(0.017)
25–34	0.088**	0.088**	0.213***	0.213***	0.013	0.012
	(0.034)	(0.034)	(0.020)	(0.020)	(0.016)	(0.016)
35–44	-0.135***	-0.135***	-0.035	-0.035	-0.004	-0.004
	(0.034)	(0.034)	(0.027)	(0.027)	(0.013)	(0.013)
45–54	-0.168***	-0.168***	-0.129***	-0.128***	-0.013	-0.013
	(0.023)	(0.023)	(0.022)	(0.022)	(0.012)	(0.012)
Panel B: Working age population						
Share of older in state	-0.547***	-0.907**	-0.670***	0.042	0.023	-0.259
	(0.164)	(0.393)	(0.224)	(0.749)	(0.121)	(0.277)
Annual growth in supply	-2.076***	-2.221***	-1.009	-0.819	1.898***	1.788***
	(0.706)	(0.745)	(0.806)	(0.892)	(0.496)	(0.476)
Direct effects						
19–24	0.742***	0.742***	0.801***	0.801***	0.070***	0.070***
	(0.029)	(0.029)	(0.024)	(0.024)	(0.017)	(0.017)
25–34	0.088**	0.088**	0.213***	0.213***	0.013	0.013
	(0.034)	(0.034)	(0.020)	(0.020)	(0.016)	(0.016)
35–44	-0.135***	-0.135***	-0.036	-0.035	-0.003	-0.004
	(0.034)	(0.034)	(0.027)	(0.027)	(0.013)	(0.013)
45–54	-0.168***	-0.168***	-0.129***	-0.128***	-0.012	-0.012
	(0.023)	(0.023)	(0.022)	(0.022)	(0.012)	(0.012)

Note: CPS 1994–2014 (JJ) and 1978–2014 (EU/UE). All columns control for state fixed effects, age fixed effects, year effects and annual growth in state real GDP per worker. Share of older is the log share of the labor force/population age 19–64 that is age 40–64. The dependent variables are the log of HP-filtered annualized monthly worker reallocation rates. Two-way clustered standard errors at state and year level.

Worker dynamics by age. Table 36 shows estimates of worker reallocation rates within age groups. The estimates are only statistically significant for the older age groups.

TABLE 36. AGING AND WORKER MOBILITY BY AGE OF WORKER

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	19–24		25–34		35–44		45–54		55–64	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: EU mobility										
LF	0.246	0.303	-0.095	-0.172	-0.540**	-0.810	-0.994***	-1.676**	-0.825***	-2.144***
	(0.154)	(0.280)	(0.188)	(0.314)	(0.237)	(0.506)	(0.279)	(0.630)	(0.222)	(0.729)
WP	0.255	0.308	-0.121	-0.175	-0.569**	-0.825	-1.070***	-1.706**	-0.915***	-2.171**
	(0.163)	(0.286)	(0.187)	(0.320)	(0.245)	(0.541)	(0.347)	(0.687)	(0.222)	(0.802)
Panel B: UE mobility										
LF	-0.094	0.153	-0.323*	-0.455	0.192	-0.000	-0.179	-0.374	-0.092	-0.448
	(0.161)	(0.344)	(0.172)	(0.326)	(0.228)	(0.404)	(0.170)	(0.360)	(0.268)	(0.422)
WP	-0.007	0.155	-0.250	-0.464	0.259	-0.000	-0.086	-0.383	0.049	-0.456
	(0.183)	(0.350)	(0.198)	(0.340)	(0.232)	(0.410)	(0.172)	(0.367)	(0.259)	(0.430)
Panel C: JJ mobility										
LF	0.056	0.499	-0.367	1.041	-0.668**	-0.858	-1.318***	-0.422	-0.389	0.037
	(0.400)	(1.272)	(0.300)	(0.891)	(0.276)	(0.651)	(0.328)	(0.972)	(0.507)	(1.323)
WP	0.086	0.565	-0.411	1.184	-0.786**	-0.976	-1.281***	-0.481	-0.951*	0.042
	(0.412)	(1.446)	(0.341)	(1.060)	(0.309)	(0.691)	(0.294)	(1.100)	(0.466)	(1.524)

Note: CPS 1994–2014 (JJ) and 1978–2014 (EU/UE). All columns control for state fixed effects, year effects and annual growth in state real GDP per worker. Share of older is the log share of the labor force/population age 19–64 that is age 40–64. The dependent variables are the log of HP-filtered annualized monthly worker reallocation rates. Two-way clustered standard errors at state and year level.

F.8 Additional details on growth

TABLE 37. AGING AND ECONOMIC GROWTH, 1978–2014

	(1)	(2)	(3)	(4)
	Labor force		Working age	
	OLS	IV	OLS	IV
40–64	-0.066	-0.090**	-0.063	-0.092**
	(0.047)	(0.040)	(0.043)	(0.039)
N	1,850	1,850	1,850	1,850
R2	0.256	0.254	0.253	0.250
R2 (within)	0.024	0.021	0.020	0.016

*Note: BEA, CPS and Intercensal Censi 1978–2014. All columns control for state and year effects. Dependent variable is growth in state real GDP per worker. Share 40–64 is the share of the labor force/population age 19–64 that is age 40–64. Instrument is share of population age 9–54 that is age 30–54 10 years earlier. Standard errors are clustered at the state and year level. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*