

Learning and Labor Market Flows

Katarína Borovičková

University of Chicago

borovickova@uchicago.edu

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Abstract

I study labor market flows in an equilibrium model with a distinct role for firm- and worker- level uncertainty, and evaluate their contribution to the labor flows. Firms experience idiosyncratic productivity shocks to which they react by adjusting the number of hired and separated workers. In addition, workers also switch jobs or leave their current firms for reasons related to the career development. Workers learn about their match quality while employed, build their careers through search for better job opportunities, and separate if they infer that their current job is not a good match. Firm-level productivity shocks impact the match quality of employed workers, which captures the idea that technology is partly embodied in workers and innovation can make some workers less suitable for the new technology. I use a large panel dataset of the labor market histories of individuals in Austria for the empirical investigation. I calibrate the model to match the aggregate labor market flows and show that the model generates dynamics which is consistent with the observed cross-sectional patterns for the job and worker flows. I use the calibrated model to evaluate the contribution of different mechanisms to the worker flows. The learning mechanism accounts for more than 50 percent of the flows which suggests that the uncertainty at the worker level plays an important role in explaining the large magnitude of the worker flows.

1 Introduction

In the developed countries, about 4-15% of workers separate from their employers on average every quarter, and about the same number of workers is hired. This constitutes a large number of workers who change their employer or labor market status every quarter. What are the driving forces of the relocation of workers? Part of these *worker flows* can be attributed to *job flows*, as firms hit by productivity and other types of shocks expand and contract their workforce, thus creating and destroying job positions. The worker flows however exceed the job flows, as part of the worker flows consists of the worker turnover in existing jobs. This suggests that it is likely that there exist other motives at the worker level which are important for workers' decision to leave.

In this paper I study the worker flows and mechanisms which drive them. I focus on three different channels. The first channel operates through changes in the firm-level productivity. The firms are subject to idiosyncratic productivity shocks to which they react by adjusting the number of hired and separated workers. The second channel is related to the individual's career. Workers build their careers through searching for a job which matches them well. When a worker starts a job, neither she nor the firm has perfect information about how well the worker is suited for the tasks required in the job. Only over time, by observing worker's output in the job, the worker-firm pair learns how good the match between them is. If they discern that the match is of a low quality, they separate and the worker continues to look for a suitable job. Finally, a worker can leave her current job when she receives a better offer from another firm. Workers will be able to search for better work opportunities while they are employed, which will not only directly generate the job-to-job transitions but the presence of this option also affects separations to unemployment. The goal of this paper is to establish the relative importance of these three channels for the worker flows.

I use a large panel dataset of the labor market histories of individuals in Austria to first motivate why these three channels are important driving forces of the worker flows, and then to calibrate the model. The data come from the social security records in Austria and contain labor market histories of almost all individuals in Austria over the period 1972-2007. The dataset contains the spells of employment and unemployment, as well as the establishment codes, and thus it is well suited to study flows of workers between different firms and the labor market states.

I first motivate the three channels. The job creation and destruction rates, defined as the sum of employment gains over plans which expand or shrink, respectively, are both simultaneously high even within narrowly defined industries. Thus, though these firms face

similar industry-specific shocks, some of them grow while other shrink. This suggests that idiosyncratic establishment-level shocks play an important role in the job flows which in turn needs to be accommodated by relocation of workers. To capture this channel in the model, the firms will be exposed to the idiosyncratic productivity shocks.

The firm-level idiosyncratic shocks are probably not the only driving force of separations. The flow of workers at the establishment level is larger than what is necessary to accommodate a net employment change in the establishments. In particular, the number of newly hired workers in a firm typically exceeds the increase in employment in this firm. Similarly, firms which shrink separate with some workers but at the same time hire some new workers. The fact that firms simultaneously hire and fire workers suggests that there is a role for the worker heterogeneity, and that there exist forces other than the firm-level productivity shocks driving separations. The workers in the model differ in how well they are suited for a particular job position. Every worker-firm pair is characterized a match quality, about which they learn gradually over time. If they discern that they are not a good fit, they separate. The worker becomes unemployed and starts to search for another job.

A large share of workers who separate from their current employers move directly to a different job without going through an unemployment spell. This points toward another reason why workers leave firms – they find a better job. In the model the workers will receive offers from other firms even while they are employed. If they accept, they move directly to a new job without an intervening unemployment spell.

I use the calibrated model to evaluate the contribution of different channels to the worker flows. The learning mechanism accounts for more than 50 percent of the flows which suggests that the uncertainty at the worker level plays an important role in explaining the large magnitude of the worker flows.

The model developed in this paper extends Moscarini (2005) who combines elements of the search and matching models in style of Mortensen and Pissarides and learning as in Jovanovic (1979). The workers who search for a job and firms which post vacancies are matched in a frictional labor market. Each match between a firm and a worker is characterized by a match quality, which is unobserved, but employed workers and their employers learn about the quality of the match by observing output that is a noisy measure of the productivity. Matches that are sufficiently likely to be of low quality end, and the worker becomes unemployed. Each firm has a constant returns to scale technology and can be matched with multiple workers. The firm is exposed to idiosyncratic, firm-specific productivity shocks. These productivity shocks not only determine the productivity level of

the firm but, importantly, impact the match quality of the employed workers. This captures the idea of technological growth is partly embodied in workers — innovation makes some skills obsolete, and existing worker might not be able to adopt the new technology.

I use the Austrian social security data to calibrate the model. The model distinguishes between job and worker flows, and therefore can be calibrate to be consistent with both. The search models which are a workhorse model used to study labor flows takes a match between a firm and a worker as a unit of analysis, and thus makes by construction makes the job and worker flows identical. A researcher then has to choose which one to take as an empirical counterpart. I use the information on the hazard rate of separation at different tenures to calibrate the learning parameters. This is a different strategy than is typically followed in the literature estimating the speed of employers' learning (for example [Altonji and Pierret \(2001\)](#) or [Lange \(2007\)](#)) which relies on the wage data.

Literature review

The learning models have been used to explain different labor market outcomes such as negative relationship between hazard rate of separation and tenure, the wage distribution or setting the relative importance of the learning by doing versus ¹. With an exception of [Pries and Rogerson \(2005\)](#), this type of model has not been used to study the worker and job flows. [Pries and Rogerson \(2005\)](#) develop a model with learning elements to examine the impact of the labor market policies on the worker flows. The match between a firm and a worker can be either good or bad, and both parties receive a signal about its quality. The learning process then takes an all-or-nothing form - each period, either the true quality of the match is revealed or no new information arrives and the posterior equals the prior. The firms then separate with workers whose match quality was revealed to be low. The model abstract from job-to-job transitions. The distinction between the job and worker flows is done based on the replacement hiring: if a worker leaves a job because their match quality was low, the firm can refill the job position by hiring a new worker. This classification does not have a direct counterpart in the data, as the data typically do not contain information on whether a worker was hired to a newly hired position or rehired to an old one. In a model where firms can hire multiple workers the measurement of the two flows in the model and in the data is the same.

Any search model which intends to account for job-to-job transitions has to incorporate

¹For example, [Jovanovic \(1979\)](#), [Moscarini \(2005\)](#), [Pries and Rogerson \(2005\)](#), [Nagypal \(2007\)](#), [Gorry \(2011\)](#), [Jovanovic and Moffitt \(1990\)](#)

search-on-the-job in some way. Even though the first models which included the on-the-job search were used to explain phenomena like decreasing relationship between the tenure and the probability of leaving a job (Burdett (1978)) or why observationally similar workers earn different wages (Burdett and Mortensen (1998)), this type of model has also been used to study the job-to-job transition of workers. However, Nagypal (2005) argues that the basic model cannot match the extent of the job-to-job transitions under plausible parametrization. The reason is that in order to generate higher job-to-job transitions, the offers have to arrive at a higher rate. But this also implies that the workers move faster through the job ladder which in turn decreases the job-to-job transitions because workers quickly get to the highest possible wage. Nagypal (2005) suggests an extension of the model which addresses this problem. In particular, if the value of the match can decrease in a way that does not induce the worker to leave her job, then the lower value of the current match increases the probability of the worker accepting an offer made by another firm. This increases the job-to-job transitions. The model proposed in this paper can explain the extent of the job-to-job transitions through learning which is consistent with the mechanism suggested by Nagypal (2005). The value of the match is continuously updated because it reflects the information that the worker and employer have about the match quality. If bad news about the match quality arrives, the value of the match to the worker decreases, but it could still be high enough so that the worker does not have a reason to separate to unemployment.

This paper relates to the stream of literature which analyzes the joint behavior of the worker and job flows. The empirical relationship between the two flows in the cross-section has been studied in Davis, Faberman, and Haltiwanger (2006) and Davis, Faberman, and Haltiwanger (2011). Using establishment-level data for the U.S. they show that there exists a strong cross-sectional relationship between job and worker flows, and this relationship is important for understanding the aggregate movements in the hires and layoffs over time. Faberman and Nagypal (2008) suggest a mechanism which can rationalize some features of the observed cross-sectional patterns, in particular, the relationship between quits, layoffs and establishment growth. They use the search and matching framework extended for on-the-job search, endogenous job destruction and differential costs of creating and refilling a vacancy. Firms respond to productivity shocks by posting new vacancies and refilling the existing ones. Separations on the worker side are driven by exogenous match destruction shocks and search on the job. The model developed in this paper also rationalizes the joint distribution of the job and worker flows but using a mechanism which focuses more on the individual-level uncertainty.

2 Empirical motivation

I start by documenting pronounced patterns in the labor flows data which motivate my theoretical work. I show the magnitudes of job and worker flows and provide evidence that these two are related yet distinct concepts. The distinction between job and worker flows will provide guidance for the calibration of shocks at the level of firms and individual matches.

For the empirical analysis, I use the Austrian Social Security Database (ASSD) dataset, described in detail in Appendix C. Although Austria is a small country, several features of the data and the Austrian economy make the use of this dataset appealing.

First, the ASSD is a rich dataset which contains labor market histories of almost all individuals in Austria over the period 1986–2007². For each individual I observe exact spells of employment and unemployment, and an establishment identifier for employed individuals. This allows me to link worker flows to establishment characteristics, and study job and worker flows using one consistent data source. The cleaned data sample includes around 2.45 million workers in 112 thousand establishments at every point in time.

Second, even though institutional regulations exist in Austria, the labor market remains flexible, with job and worker flows similar to those in the U.S. labor market. Moreover, aggregate labor market statistics in Austria have been stable during the analyzed period, with only a very limited impact of the business cycle on the labor market flows. Since the model I develop abstracts from aggregate productivity shocks and generates steady state distributions of firms and worker flows, Austria provides a good laboratory for this type of analysis.

2.1 Labor market and institutional setting in Austria

The Austrian labor market is characterized by a relatively large turnover of jobs and workers and a low unemployment rate. Pries and Rogerson (2005) use a variety of sources for job and worker flows in the U.S. and Europe to show that even though the magnitude of job turnover is similar in continental Europe and the U.S., worker turnover in the U.S. is higher than in Europe by a factor of at least 1.5. In this respect, worker turnover in Austria is high relative to other countries in continental Europe, as around 9% of workers separate from their employers every quarter and about the same number is hired, compared to 11% in the U.S.

²The dataset starts in 1972, but it underreports unemployment spells for the 1972–1985 period. Since flows of workers between employment and unemployment are important in my analysis, I use a subsample which starts in 1986.

The average unemployment rate in Austria during the 1986–2007 period was 4.5% according to the Labor Force Survey, one of the lowest in Europe. The ASSD is based on administrative data, and thus measures registered unemployment. The unemployment rate according to this measure reaches 6.5% for the same period, which is still lower than unemployment rates observed in large European economies.

A useful feature of the Austrian labor market is the absence of a pronounced business cycle during the period covered by the data. Macroeconomic aggregates and labor market flows have little cyclical variation during this period. There were 2 quarters with a negative rate of GDP growth but this was not reflected in the analyzed labor market indicators.

Worker and job flows are crucially influenced by existing regulations of worker displacement that lead to financial and nonfinancial costs of firing. In this respect, Austria is a country with relatively low firing costs, at least in comparison to continental Europe, and I will abstract from the firing cost in my model. The analysis of the impact of firing costs and other institutional labor market frictions remains an interesting area of further research.

The main source of the direct financial costs of displacing a worker is the severance payment to the worker. Currently, two systems regulating the severance payment coexist in Austria: an “old” experienced-based system applies to all contracts signed before December 31, 2002, while the “new” contribution-based system covers all contracts signed after this date. In the old system, if a contract is terminated by the employer, a worker with at least 3 years of tenure becomes eligible for the severance payment, starting with a two-month salary and gradually increasing with the tenure of the displaced worker.³ In the new system, employers do not make any direct severance payments to the displaced worker. Instead, employers contribute a certain percentage of workers’ gross wages into a severance fund. In case of a dismissal, the worker receives a payment from the severance fund.⁴

There is an additional layoff tax for displacing a worker who is older than 50 years and has been continuously employed in the given firm for at least 10 years.⁵ The exact amount of the tax depends on the tenure and years to retirement but it can reach 170% of the monthly salary for men and 60% for women.

Job losers are eligible for unemployment benefits if they have worked for at least 12 months

³The severance payment rises to 3 months for workers with 5 years of service, to 4 months after 10 years, 6 months after 15 years, 9 months after 20 years and 12 months after 25 years.

⁴The contribution is 1.53% of worker’s gross salary. After a dismissal, the worker can leave the benefit in the fund or have it paid out as a lump sum, but the lump sum payment is available only to workers who contributed for at least 3 years into the fund.

⁵This law was introduced in 1996. Schnalzenberger and Winter-Ebmer (2009) provide a more detailed description of the law.

during two years preceding the job loss. The benefits on average cover 55% of worker’s previous net wage which provides strong incentives to register. The duration of the benefits depends on the number of months the worker has worked in the past 5 years, and typically varies between 20 and 30 weeks.

2.2 Establishment-level idiosyncratic shocks

An important driving force of the worker relocation is the firm labor demand. In response to productivity or demand shocks, firms need to increase or decrease their employment, which must be accommodated by hiring new workers or separating with existing ones.

The shocks that a firm faces could be different in nature, but, as I’ll argue below, the establishment-level idiosyncratic shocks appear to be the most important. Therefore, in the model the firms will be exposed only to the firm-level idiosyncratic productivity shocks.

To separate the idiosyncratic shocks from the aggregate shocks or industry-specific shocks, I look at the number of jobs created and destroyed within particular industries. I find that within one quarter, many establishments expand while other establishments decrease their employment within the same industry which I interpret to mean that the idiosyncratic shocks play an important role.

I measure the number of new and destroyed jobs through the job creation and destruction measures defined in [Davis, Haltiwanger, and Schuh \(1998\)](#). The job creation and destruction at time t is $JC_t = \sum_e \max(E_{e,t} - E_{e,t-1}, 0)$ and $JD_t = -\sum_e \min(E_{e,t} - E_{e,t-1}, 0)$, where $E_{e,t}$ is the number of employees in establishment e at time t . To express them in rates, I divide them by the measure of employment at time t .

Table 1 shows the quarterly job creation and destruction rate in different industries, averaged over the period 1986–2007. The rates vary within 2–5% in most of the industries. Agriculture, accommodation and construction are three industries which have unusually large rates of the job creation and destruction, while utilities has an exceptionally low rates at only about 1% per quarter. The uniformly high magnitudes of the job flows within these industries point toward the importance of the idiosyncratic component of the firm labor demand.

A possible criticism is that this division is rather coarse. I therefore look at the job creation and destruction rates within a narrowly defined industries using the 4-digit NACE industry code (Classification of economic activities in the European community). There are 41748 distinct industries in the database. Table 2 summarizes the distribution of the job creation and destruction rates in these narrow industries. The pattern which emerges

is that most of these narrowly defined industries experience simultaneous job creation and destruction. Thus again, even within narrowly defined industries, shrinking establishments coexist with growing establishments, which suggests that the firm-level idiosyncratic shocks play an important role.

2.3 Job and worker flows

Job and worker flows are closely related but nevertheless remain distinct concepts. Job flows, which represent creation and destruction of job positions, necessarily lead to worker reallocation. However, a substantial part of worker flows is generated by workers leaving and accepting existing job positions, and thus does not generate job flows.

I use establishment growth rates to measure job flows. This measure only captures *net* job flows at the level of individual establishments. In the theoretical model, I specify the production technology at the level of individual firms, and do not assign specific roles to individual job positions within a firm. I can therefore abstract from the simultaneous creation and destruction of distinct job positions within a firm. Worker flows are measured by hiring and separations rates.

I follow the [Davis, Haltiwanger, and Schuh \(1998\)](#) methodology and define the growth rate of an establishment e at time t as $g_{et} = (E_{e,t} - E_{e,t-1}) / Z_{et}$, where $E_{e,t}$ is the number of employees and $Z_{et} = 0.5 (E_{e,t} + E_{e,t-1})$ is a measure of the establishment size. I similarly define measures of establishment-level hiring and separation rates to be $h_{et} = H_{et} / Z_{et}$ and $s_{et} = S_{et} / Z_{et}$ where H_{et} and S_{et} is the number of hired and separated workers in establishment e at time t , respectively. To analyze the relationship between worker and job flows at the establishment level, I sort establishments into narrow bins based on their growth rate and calculate the employment-weighted hiring and separation rates for each bin. In this way, I allow for a non-linear relationship between these flows.

I start by documenting that the job and worker flows are closely related, yet not identical. I use establishment growth rate to measure the job flows, and the hiring and separation rates to measure the worker flows. I follow the [Davis, Haltiwanger, and Schuh \(1998\)](#) methodology and define the growth rate of an establishment e at time t as $g_{et} = (E_{e,t} - E_{e,t-1}) / Z_{et}$, where $E_{e,t}$ is the number of employees and $Z_{et} = 0.5 (E_{e,t} + E_{e,t-1})$ is the measure of the employer size. I similarly define measures of establishment-level hiring and separation rates to be $h_{et} = H_{et} / Z_{et}$ and $s_{et} = S_{et} / Z_{et}$ where H_{et} and S_{et} is the number of hired and separated workers in establishment e at time t . To analyze the relationship between worker and job flows at the establishment level, I sort establishments into narrow bins based on their growth

rate and calculate the employment-weighted hiring and separation rates for each bin. This way I allow for a non-linear relationship between these flows.

Figure 1 shows the tight link between job and worker flows. Job flows, measured by the establishment growth rate, are depicted on the horizontal axis while hiring and separations as shares of establishment employment are depicted on the vertical axis.

The hiring rate is increasing almost one-for-one with the establishment growth rate in growing establishments. Part of this relationship is mechanical, as establishment growth can only be generated by new workers joining the firm. However, the hiring rate is much higher than what is necessary to accommodate the growth rate, implying that even in growing firms, separations play an important role. The separation rate is almost a mirror image of the hiring rate. In shrinking firms, the separation rate exceeds the contraction rate, with the hiring rate being still fairly high. These patterns are remarkably similar to those documented by Davis, Faberman, and Haltiwanger (2006) for the U.S. data, which also suggests that the Austrian labor market is not too different from the labor market in the U.S. along these dimensions.

The relationship between job and worker flows is robust to inclusion of the establishment fixed effects,⁶ as the dotted lines in Figure 1 indicate. The pooled estimates, represented by the solid lines in the graph, show the hiring and separation rate in an average establishment with a given growth rate. The estimated relationship thus could be driven by the composition of establishments in each growth bin. For example, the pooled regression may ignore unobserved heterogeneity in the volatility of firm-level shocks. More volatile establishments may have different mean hiring and separation rates and, at the same time, their observed growth rates would be mechanically sorted into both tails of the growth rate distribution. The establishment fixed effects absorb the heterogeneity in mean hiring and separation rates, and isolate the within-establishment variation. The fixed-effect regression thus measures how an individual establishment varies its hiring and separation policies depending on the size of the employment change. The fact that the cross-sectional pattern remains similar indicates that the idiosyncratic shocks at the establishment level are the key driving force behind this figure.

Overall, about one third of the worker flows can be explained by changes in establishment sizes, and thus is driven by firm-level idiosyncratic shocks.⁷ In the model, firms will be

⁶I run a regression of the hiring and separation rates on the full set of dummy variables for the growth rate bins, where I also include establishment fixed effects. The figure then depicts the coefficients for the dummy variables.

⁷The R^2 from the regressions of the hiring and separation rates on the full set of dummy variables for growth rate bins is 0.34 and 0.28, respectively.

exposed to idiosyncratic technology shocks to which they will respond by adjusting the firm size. A positive technology shock will increase the willingness of the firm to hire new workers. At the same time, the firm will tolerate workers with lower worker-specific productivity components. Both effects will tend to increase the growth rate of the firm but the latter effect will generate a counterfactually declining separation rate. Firm-level shocks alone cannot generate the observed pattern for the separation rate.

2.4 Worker flows between labor market states

Establishments are engaged in simultaneous hiring and separations along the entire range of the growth rates. Workers leave firms which do well and grow, and other workers join firms which shrink in reaction to a negative shock. This suggests that is an economic forces other than firm-level productivity shocks that affect workers' decision to end a match with one firm and join another firm or go to non-employment.

A prominent motive for the worker reallocation are career concerns. Workers build their careers through search for suitable employment opportunities and in doing so they relocate across firms and labor market states. Indeed we will see that movements of workers between firms, and between employment and non-employment are all important components of the worker flows.

A unique feature of the dataset is the possibility to track individual workers across different labor market states. I can therefore utilize the information on the subsequent labor market state to evaluate whether the separated workers become unemployed, continue in another job, or alternatively, whether they leave to maternity or retirement. Similarly I can use the information on the previous labor market state to decompose the hiring rate according to where workers come from. Table 3 shows the decomposition of the hiring and separation rates according to the previous and subsequent status. For some workers, it is not possible to observe the previous and/or subsequent labor market state in the database, which happens for example if the is out of labor force, and therefore the decomposition does not sum up to the hiring and separation rate.

We observe that the worker flows between employment and unemployment is of the same magnitude as the flow of workers between the different jobs. Every quarter, about 2.4% of workers are hired from unemployment, and about the same number is hired from another job. Similarly, 2.4% of workers separate to unemployment every quarter, and about the same of workers leave their current job to start working in a new job. To capture these flows in the model, workers will have an option to separate to unemployment at any time. Moreover,

workers will receive offers from firms even while they are employed. If they accept, they can start working in a new firm without going through an unemployment spell.

2.5 Tenure length

Workers build their careers through search for suitable jobs. However, when they start a new job, they do not have perfect information about how well they will be suited for the tasks. Only over time they learn how good their match with the firm is, and if they find it unsatisfactory, they decide to leave the job. Learning about the match quality is thus potentially an important determinant of worker's decision to separate.

Models which introduce learning about the match quality predict that the hazard rate of separation is decreasing in worker's tenure. This prediction is indeed confirmed by the data, as Figure 2 shows.⁸ Learning alone, however, would imply that the hazard rate of separation should ultimately converge to zero, as workers at long tenures are reliably identified as good matches. The nonvanishing hazard rate at long tenures observed in the data is then typically captured by an exogenous separation shock (as in Moscarini (2005) or Nagypal (2007)) whose intensity is independent of tenure.

Tenure, which is a statistic related to the particular match between a worker and a firm rather than the firm itself, is thus an important determinant of separation risk. Moreover, separation risk across tenures interacts with job flows. Figures 3 and 4 show the hazard rate of separation at different tenures in establishments with different growth rates. Although one might expect that in growing firms, the hazard rate will be the same or lower than the hazard rate in firms which do not grow, I find in the data that the entire hazard rate curve shifts up with the establishment growth rate.⁹

The hazard rate curve also shifts up with the contraction rate in the shrinking firms. While one might have expected this relationship, it is again important to notice that workers with all tenures face a higher risk of being separated, and the hazard rate curves shift up almost parallelly.

The pattern of hazard rates is not easy to reconcile with the learning about the match quality mechanism alone: in the learning models, workers with long tenures are believed to be ones with high-quality matches, and thus would face a negligible hazard rate of separation

⁸There is a spike in the hazard rate of separation at 3 years of tenure, which is the time when a worker under the old social security system becomes available for the severance payment.

⁹Notice that this is not implied by the fact that growing establishments have a higher separation rate. The increase could be due to the composition of workers, as fast-growing firms have a higher share of low-tenured workers who face the highest hazard rate of separation.

regardless of the changes in economic conditions of the firm. In addition, adding an exogenous separation shock will not help explain this pattern, either, as the hazard rate of separation for workers with long tenures would be given by the exogenous separation rate, irrespective of the firm’s growth rate.

These results illustrate that firm-specific and match-specific forces driving worker flows are not orthogonal and interact. In this paper I introduce *technology-adoption shocks* as a mechanism that captures this interaction. Firm-level shocks, both positive and negative ones, not only change the productivity of the firm but also make some skills obsolete. This feature of the model disentangles firm-level and worker-level risk, and constitutes the crucial component of the model that captures the dynamics of the hazard rate of separation across growth rates and tenures.

3 Model

The model is an extension of Jovanovic (1979) and Moscarini (2005). The economy is populated by a continuum of risk-neutral workers who search for jobs and a continuum of profit-maximizing firms that post vacancies in a labor market with search frictions. Employed workers and their employers learn about the quality of the match by observing a stream of stochastic output that is a noisy measure of the productivity. Matches that are sufficiently likely to be of low quality end, and the worker becomes unemployed. Workers search for new jobs both when unemployed and on the job, and choose to accept offers that improve their current position.

Each firm has a constant returns to scale technology and can be matched with multiple workers. The firm is exposed to idiosyncratic, firm-specific productivity shocks. These productivity shocks not only determine the productivity level of the firm but, importantly, impact the match quality of the employed workers. This captures the idea of technological growth is partly embodied in workers — innovation makes some skills obsolete, and existing worker might not be able to adopt the new technology.

To hire new workers, firms have to post vacancies which are then matched with workers searching for a job in a matching market. It is increasingly more costly for a firm to hire more workers at a given instant and thus firms will post finite number of vacancies, which will determine the scale and the size of a firm.

Given my focus on idiosyncratic shocks that drive most of the job transitions, I abstract from aggregate uncertainty. In the stationary equilibrium, I can find the distribution of firms

over their firm-specific productivity, and the distribution of workers over their employment status and match quality.

3.1 Preferences and production technology

There is a measure one of infinitely-lived worker with linear preferences over the consumption streams

$$E_0 \int_0^\infty e^{-\rho t} c(t) dt.$$

Since workers are risk-neutral, an employed worker consumes her wage while an unemployed worker consumes her unemployment benefits. An unemployed worker searches for a job, and when contacted, decides whether to accept an offer. An employed worker decides whether to stay in the current job or leave to unemployment, and if contacted by an outside firm, whether to accept this offer.

Employed workers are engaged in the production of the consumption good. There is a measure one of profit-maximizing competitive firms. A firm k is characterized by its time-varying productivity level $A_k(t)$. Firms have constant returns to scale production technology with labor as the only input. Thus, for workers to work in the same firm k at time t only means that they share the same firm productivity level $A_k(t)$.

The output of a worker l employed in the firm k depends both on the firm's productivity $A_k(t)$ and on a match-specific productivity $\mu_{lk}(t)$ which measures whether the worker is suitable for the particular technology in place. The worker produces

$$dy_{lk}(t) = A_k(t) dt + dx_{lk}(t),$$

where $x_{lk}(t)$ follows a Brownian motion with an unobservable match-specific drift $\mu_{lk}(t)$,

$$dx_{lk}(t) = \mu_{lk}(t)dt + \sigma_x dW_{lk}(t),$$

where $dW_{lk}(t)$ is independent across workers, firms and time. The value of $A_k(t)$ is specific to the firm while $\mu_{lk}(t)$ and the shock $dW_{lk}(t)$ are specific to the match between the worker l and the firm k . The value of $\mu_{lk}(t)$ is unobserved because the shock $dW_{lk}(t)$ generates noise around the true value of $\mu_{lk}(t)$. The worker – firm pair infers the value of $\mu_{lk}(t)$ by solving a filtering problem, described in section 3.3. The values of $A_k(t)$, $dy_{lk}(t)$ and $dx_{lk}(t)$ are observable to both the worker and the firm.

3.2 Productivity shocks

Firms are exposed to idiosyncratic shocks to their productivity. The productivity level of the firm is however partly embodied in the workers employed in the firm. That is, a better technology does not necessarily make every worker in the firm more productive, as some workers will not be able to implement it. As a result, it can happen that workers who were a good match before the new technology has arrived can suddenly become less valuable. I will capture this mechanism through *technology-adoption shocks*: a change in the firm-level productivity can affect the quality of the match.

The firm-specific productivity $A_k(t)$ follows a finite-state Markov process with $A_k(t) \in \mathcal{A} \equiv \{A_1, \dots, A_I\}$ and a matrix of transition rates Ω .

The match quality $\mu_{lk}(t)$ can attain 2 values, $\mu_H > \mu_L$. This value is drawn when the match is formed from a known distribution F_μ where the probability that the match quality is high is p_0 .

The match quality μ is not fixed throughout the duration of the match, and its changes are linked to changes in the firm-specific productivity A . On arrival of a new firm productivity shock, i.e. when there is a change from A_i to A_j with $i \neq j$, a *high quality match* can turn into a *low quality match* with a certain probability γ . Since μ is unobservable, the switch from the high to low quality is unobservable as well. This is the *technology-adaption shock*: not all workers are able to implement the new technology. Some abilities that workers have can become obsolete for the new technology and thus matches which could have been good before the change suddenly become less valuable.

3.3 Learning

The value of the match quality between a worker l and a firm k , $\mu_{lk}(t)$, is unobservable, but the worker-firm pair forms beliefs about its value by filtering the realizations $dx_{lk}(t)$. To simplify the notation, in what follows I drop the subscripts lk which describe the match between the firm and the worker.

Since μ can attain only 2 values, $p(t)$, the probability that μ is high, is a sufficient statistic for the learning problem. I distinguish two cases when deriving the learning formula: 1) update of beliefs based on observing a new output realization $dx(t)$, 2) update of beliefs after observing a change in the firm productivity level from A_i to $A_j, i \neq j$. In the first case, the standard [Wonham \(1964\)](#) result implies that $p(t)$ follows a diffusion process

$$dp(t) = \sigma_p(p(t)) d\bar{W}(t) \quad (1)$$

where

$$\begin{aligned}
\sigma_p(p) &= p(1-p)s \\
s &= \frac{\mu_H - \mu_L}{\sigma_x} \\
d\bar{W}(t) &= \frac{1}{\sigma_x} (dx(t) - \mu_H p(t) - \mu_L (1-p(t)))
\end{aligned} \tag{2}$$

Here $d\bar{W}(t)$ is a standard Brownian motion under the information set of the worker and the firm. The innovation process $d\bar{W}(t)$ is the normalized difference between the realized output $dx(t)$ and the expected output $\mu_H p(t) + \mu_L (1-p(t))$.

Equation (1) describes how worker and firm update their belief $p(t)$ after observing a new realization of the output $dx(t)$. If the realization of the output is higher than expected, the belief $p(t)$ that the quality of the match is high is updated upward, i.e. $dp(t) > 0$, otherwise it is updated downward. The magnitude of the belief's update $|dp(t)|$, or the speed of learning, depends on two factors, the signal-noise ratio s and the precision of the belief. A higher signal-noise ratio implies faster learning: it is easier to infer which distribution the realization $dx(t)$ is drawn from if the means of the distributions are very different ($\mu_H - \mu_L$ is large), or when the realizations are mostly drawn from a narrow neighborhood of the true mean (σ_x is small). The learning is faster when the current belief is less precise (p is close to $1/2$). This is a typical result from the Bayesian learning — the weight that is put on new information relative to current knowledge is higher when only little is known, i.e. when the current belief is not precise.

Although workers of both match qualities start with the same prior belief, the belief about the match quality of the high and low type will, in expectation, drift to one and zero, respectively. Given that the model is calibrated so that workers with a sufficiently low $p(t)$ separate, the average cross-sectional match quality of the workforce increases with tenure. Absent technology-adoption shocks, long-tenured workforce would consist primarily of the high-quality matches with negligible hazard rates of separation.

The technology-adoption shocks that augment the match quality of individual workers counteract this force. When the firm receives a new productivity shock, i.e. it switches from A_i to A_j for $i \neq j$, each worker in this firm faces a probability γ of that her match quality can switch from high to low. In this case, the belief is updated using the Bayes formula.

Given the prior belief p , the posterior belief p' is given by

$$\begin{aligned} p' &= p \Pr[\mu' = \mu_H | \mu = \mu_H] + (1 - p) \Pr[\mu' = \mu_H | \mu = \mu_L] \\ &= p(1 - \gamma) \end{aligned} \tag{3}$$

The probability that a high-quality match is not affected by the change in the productivity is $1 - \gamma = \Pr[\mu' = \mu_H | \mu = \mu_H]$. Since the technology-adoption shock does not turn the low-quality matches into high-quality, it holds that $\Pr[\mu' = \mu_H | \mu = \mu_L] = 0$.

Notice that the posterior belief p' is lower than the prior belief for all p , and the posterior belief moves closer to $1/2$ for high prior beliefs p . Thus, a productivity shock, regardless whether good or bad, can make the perceived match quality more uncertain — the firm-worker pair has to learn again whether the worker is suitable for the particular technology in place. The ranking of workers in the firm does not change: better matches remain better. However, the expected productivity of workers who switched from being high-quality matches to being low-quality matches will drift downward over time.

3.4 Search and matching

The firm-worker pairs are formed at a matching market where workers searching for a job and vacancies posted by firms are brought together to form matches. This process is described by an aggregate matching function which at every instant determines the number of matches as a function of the number of searching workers and the aggregate number of vacancies. A matching function is a simple device capturing the idea that search is a costly process for both workers and employers, who must spend time and resources to find a productive match.

The number of meetings between posted vacancies and workers searching for a job is described by an aggregate matching function,

$$M = M(S, V)$$

where S is the number of searchers and V is the total number of posted vacancies. I assume that $M(\cdot, \cdot)$ is increasing, concave and homogenous of degree one in (S, V) . The employed workers continue receiving offers from other firms, and thus the total number of searchers S includes both unemployed and employed. Their shares are appropriately weighted because the employed receive offers at a different intensity.

At every instant, the worker and the firms that are matched are randomly drawn from

the pool of searchers and vacancies, respectively, and hence the job-finding rate for the unemployed f_u and vacancy-filling rate q are given by

$$f_u = \frac{M(S, V)}{S}, \quad q = \frac{M(S, V)}{V}. \quad (4)$$

By the constant returns to scale assumption, the job-finding and vacancy-filling rates are only a function of the market tightness ratio $\theta \equiv V/S$,

$$f(\theta) = M(1, \theta), \quad q(\theta) = M(1/\theta, 1).$$

The matching function thus determines the frequency at which a worker receives offers from other firms, which a worker takes as given.

Workers, both employed and unemployed, are contacted by a firm and choose to accept an offer which improves their current position. If an employed worker accepts an offer, she can move directly to another job without undergoing an unemployment spell. This mechanism captures the job-to-job movements which, as described in Section 2, account for about one quarter of all new hires.

The employed workers receive offers at different rates: unemployed at the rate f_u while employed at the rate $f_e = \psi f_u$, where $0 \leq \psi \leq 1$. Therefore, the employed workers are less effective in the search and there is a benefit of going through an unemployment spell. When contacted by an outside firm, an employed worker decides whether to accept or reject the offer. If she accepts, she leaves the current firm and draws a new match-specific value μ from the distribution F_μ .

3.5 Value functions

The assumption of the constant returns to scale technology allows me to study a match between a firm and a worker without keeping track of other workers employed in the firm.

Since the sufficient statistic for the belief about the match quality is p and the firm is characterized by its productivity level, the state for the firm-worker match is (A, p) . I specify the value functions for the unemployed U , the value of a match to the firm $J(A, p)$, and the value to the worker $W(A, p)$.

I formulate the value functions assuming that the worker-firm pair agrees on separation to unemployment and then verify that this is indeed the case. I will look for an equilibrium where the wage rate is determined through the Nash bargaining, with dissolution of the

match as a threat point: if they do not agree, the worker becomes unemployed and the job is destroyed. This follows [Pissarides \(2000\)](#).

When unemployed, the worker consumes her unemployment benefits b and searches for a job. She gets contacted by a firm at the rate f_u . With probability $\bar{v}_j$ the offer is coming from a firm with the productivity level A_j . Here f_u and $\bar{v}_j, \forall j$ are endogenous equilibrium objects which a worker takes as given: $\bar{v}_j$ are determined by the distribution of vacancies over firms with different productivities, and f_u by the labor market tightness. The unemployed worker decides whether to accept an offer. If she does, she draws a match-specific productivity μ from F_μ . The value function is given by

$$\rho U = b + f_u \sum_{j=1}^N \bar{v}_j \max(W(A_j, p_0) - U, 0), \quad (5)$$

where p_0 is the prior belief that the match quality is high. If the value of accepting the offer $W(A_j, p_0)$ is lower than the value of being unemployed, the worker turns the offer down. In equilibrium, firms do not post vacancies that would not be accepted and thus $\bar{v}_j = 0$ if $W(A_j, p_0) < U$.

An employed worker consumes her wage $w(A, p)$ and decides whether to stay employed in the current firm or quit to unemployment, and, conditional on receiving an outside offer, whether to accept it or not. The flow value of the match for the worker is

$$\rho W(A_i, p) = \max\{\rho U, \rho W^{stay}(A_i, p)\} \quad (6)$$

$$\begin{aligned} \rho W^{stay}(A_i, p) &= w(A_i, p) \\ &+ f_e \sum_j \bar{v}_j \max[W(A_j, p_0) - W(A_i, p), 0] \\ &+ \frac{1}{2} \sigma_p^2(p) \frac{\partial^2 W(A_i, p)}{\partial p^2} \\ &+ \sum_{j \neq i} \omega_{ij} (W(A_j, p') - W(A_i, p)) \end{aligned} \quad (7)$$

where p' is given in (3) and ω_{ij} are elements of the intensity matrix Ω . The value of quitting to unemployment is ρU . The value of staying in the firm equals the wage flow plus the value of receiving an outside offer, gain from learning, and the benefit from receiving a new productivity shock A_j . The worker is contacted by an outside firm at the rate f_e , and with probability $\bar{v}_j$ this offer comes from a firm with a productivity level A_j . Since the quality of

the job in the new firm is unobserved, the belief is reset to p_0 , and the value of accepting an offer is $W(A_j, p_0)$. The worker decides to accept if it is higher than the value of staying with the current employer, $W(A_j, p_0) > W(A_i, p)$. The firm with the current productivity level A_i receives a new productivity A_j at the rate ω_{ij} . For $i \neq j$ this also indicates that the high-quality matches can switch with the probability γ , and therefore the belief is updated to p' and worker's value of staying in the firm is $W(A_j, p')$.

The value of the match to the firm is similar:

$$\rho J(A_i, p) = \max \{0, \rho J^{stay}(A_i, p)\} \quad (8)$$

$$\begin{aligned} \rho J^{stay}(A_i, p) &= \bar{\mu}(A_i, p) - w(A_i, p) \\ &- f_e \sum_j \bar{v}_j \mathbf{I}_{W(A_j, p_0) - W(A_i, p) > 0} J(A_i, p) \\ &+ \frac{1}{2} \sigma_p^2(p) \frac{\partial^2 J(A_i, p)}{\partial p^2} \\ &+ \sum_{j \neq i} \omega_{ij} (J(A_j, p') - J(A_i, p)), \end{aligned} \quad (9)$$

where $\mathbf{I}_x$ is an indicator function for event x , and $\bar{\mu}(A_i, p) = A_i + p\mu_H + (1-p)\mu_L$ is the expected output flow. The firm decides to stay in a match with the current worker as long as the value of the match is greater than zero. The value of the match equals the expected output flow minus the wage and the loss from the separations due to the worker accepting an outside offer. The last two terms represent the gain from learning and the benefits from receiving a new productivity shock. These terms are analogous to the worker's value function. The term arising due to search on the job is different from the corresponding term in worker's value function: when the worker decides to accept an outside offer, i.e. when $\mathbf{I}_{W(A_j, p_0) - W(A_i, p) > 0} = 1$, the firm loses the entire value of the match $J(A_i, p)$.

3.6 Wage

A realized match yields rents which need to be shared through the wage. I assume that the wage is determined through the Nash bargaining where the dissolution of the match is taken as a threat point: if a worker and a firm do not agree about the wage, the match ends, the worker becomes unemployed and the job position is destroyed. The wage is continuously

renegotiated when new information arrives and maximizes the Nash product

$$w(A_i, p) = \arg \max_w (W(A_i, p) - U)^\beta J(A_i, p)^{1-\beta}.$$

The first-order condition with respect to the wage yields

$$\beta (W(A_i, p) - U) = (1 - \beta) J(A_i, p). \quad (10)$$

Using equation (10) and the value functions (7), (9), one can find an expression for the wage

$$\begin{aligned} w(A_i, p) = & \rho U + \beta (\bar{\mu}(A_i, p) - \rho U) \\ & - \beta f_e \sum_{\{j: W(A_j, p_0) - W(A_i, p) > 0\}} \bar{v}_j J(A_i, p_0) \\ & - (1 - \beta) f_e \sum_{\{j: W(A_j, p_0) - W(A_i, p) > 0\}} \bar{v}_j (W(A_j, p_0) - W(A_i, p)) \end{aligned} \quad (11)$$

The first two terms in (11) are standard: the wage is worker's reservation value ρU plus the fraction β of the net surplus she produces on the job. The last two terms arise due to search on the job and reflect that the benefit from receiving an outside offer goes to the worker, while the firm bears the costs when a worker leaves. Due to the Nash bargaining, the firm and the worker share all costs and benefits. Thus, in the matches where a worker accepts an outside offer if she gets one, the worker bears a β -fraction of the firm's expected loss (the second line) and the firm takes a fraction $(1 - \beta)$ of worker's expected gain from accepting an outside offer (the third line).

Equation (10) implies that the worker and the firm agree on the separation to unemployment: a worker separates to unemployment when her value of staying in the job falls below the value of unemployment, $W(A_i, p) < U$. Similarly, a firm wants to end the match when the value of the match is negative, $J(A_i, p) < 0$. Equation (10) implies that $W(A_i, p) < U \iff J(A_i, p) < 0$, which verifies the conjecture in Section 3.5 was correct.

Finally, it is worth noting that the expected output flow $\bar{\mu}(A_i, p)$ is linear in the belief p , and thus (11) implies that the wage is also linear in p .

3.7 Vacancy posting

A firm has to post vacancies to hire new workers. The hiring process is costly, and it is increasingly more expensive to hire more workers at once. Thus, the cost of posting vacancies

is convex, as for example in [Garibaldi and Moen \(2010\)](#) or [Kaas and Kircher \(2010\)](#).

Denote $C(v)$ the costs of posting v vacancies. $C(v)$ is increasing and convex, with $C(0) = 0$. To determine how many vacancies to post, a firm maximizes the expected return net of posting cost,

$$\max_{v \geq 0} [vqJ(A_i, p_0) - C(v)],$$

where q is the vacancy filling rate which is determined in equilibrium and taken as given by the firm, and $J(A_i, p_0)$ is the value of a newly hired worker for the firm. The first-order condition gives

$$C'(v) = qJ(A_i, p_0) \text{ if } v > 0. \quad (12)$$

As long as the value of a new worker is positive, the firm posts vacancies up to the point where the marginal cost of posting a vacancy equals the expected value from filling the vacancy. The number of posted vacancies, $v(A_i)$, only depends on the firm's productivity level A_i . A firm posts no vacancies if $J(A_i, p_0) = 0$.

Throughout the paper I assume a specific functional form for the cost function, $C(v) = cv^\eta$.

The convexity of the hiring cost determines the firm size and governs the firm growth. As long as there is a positive surplus from a match to share, a firm wants to hire more workers. Due to the assumption of linear production technology, if the vacancy posting cost was linear with $\eta = 1$, a firm posts infinitely many vacancies if $c < J(A_i, p_0)$ and zero if $c > J(A_i, p_0)$. Thus, the convexity of the hiring cost guarantees that the firm posts finite number of vacancies which then determines the firm size. Also, the convexity of the hiring costs governs the firm growth. For each productivity level A , there is a steady state value of employment at which the firm-level separation rate equals firm-level hiring rate. After receiving a new productivity shock, a firm starts a transition toward the new steady level of employment. The speed of the transition is governed by the convexity of the hiring costs due to which it is expensive for a firm to hire many workers at once and therefore a firm would choose to spread out the hiring over a longer period.

3.8 Steady state equilibrium

The number of matches together with the aggregate number of vacancies and searchers then determines the job-finding and vacancy-filling rate, the objects that have been so far treated as given in the decision problems of the workers and firms. I focus on a steady state equilibrium.

3.8.1 Distribution of workers and the number of searchers

The equilibrium objects $f_u, q, \bar{v}_i$ depend on the aggregate variables S and V , the values of which depend on the joint distribution of beliefs p and firms' productivity levels A in the economy. While the distribution of firms' productivity levels determines the distribution of vacancies, the joint distribution of (A, p) determines the unemployment rate.

To simplify the exposition, define an employment set $\mathcal{E} \subset (\mathcal{A}, [0, 1])$ as a set of all pairs (A_i, p) for which a match can exist,

$$\mathcal{E} = \{(A_i, p) : A_i \in \mathcal{A}, \quad p \in [0, 1], \quad \underline{p}(A_i) \leq p \leq 1\}.$$

Let $g(A_i, p)$ be the density¹⁰ of workers with belief p employed in firms with the productivity A_i at time t . For $(A_i, p) \notin \mathcal{E}$, the match does not exist, and thus $g(A_i, p) = 0$. For almost all $(A_i, p) \in \mathcal{E}$, the Kolmogorov forward equation describes the dynamics of this density. Imposing that the distribution is time-invariant gives:

$$\begin{aligned} \frac{d}{dt}g(A_i, p) = 0 &= \frac{d^2}{dp^2} \left[\frac{1}{2} \sigma_p^2(p) g(A_i, p) \right] \\ &- \left[f_e \sum_{\{j: W(A_j, p_0) - W(A_i, p) > 0\}} \bar{v}_j + \sum_{j \neq i} \omega_{ij} \right] g(A_i, p) \\ &+ \sum_{j \neq i} \omega_{ji} g\left(A_j, \frac{p}{1 - \gamma}\right) \frac{1}{1 - \gamma} \end{aligned} \quad (13)$$

The first term on the right measures the flow into and out of $g(A_i, p)$ from changes in the belief p . Workers flow into (A_i, p) from some $\hat{p} < p$ after observing a higher than expected output flow, or from $\hat{p} > p$ after lower than expected realization of the production flow. At the same time, some workers flow out of (A_i, p) due to updating the beliefs from p to $\hat{p} \neq p$. The variance $\sigma_p^2(p)$ measures the speed with which the beliefs move over p . All these flows are netted in by the first term.

Learning is not the only channel through which the density at (A_i, p) changes. The term in the second line captures the fact that a density at (A_i, p) falls at the rate $f_e \sum_{\{j: W(A_j, p_0) - W(A_i, p) > 0\}} \bar{v}_j$ due to search on the job, and at the rate $\sum_{j \neq i} \omega_{ij}$ due to outflow caused by firms receiving new productivity shocks. At the same time, the density at (A_i, p) gains workers employed in firms with productivity $A_j \neq A_i$ which received a new productivity shock A_i , and have

¹⁰I call g the density even though it does not integrate to one; it integrates to the employment rate in the economy which I use to determine the equilibrium unemployment rate.

updated their beliefs using (3). The mass of workers whose belief is updated to p after firm's productivity changes from A_j to A_i is $g\left(A_j, \frac{p}{1-\gamma}\right)$, where $p/(1-\gamma)$ is inverse of (3). Since equation (3) maps an interval $[0, 1]$ into an interval $[0, 1-\gamma]$, I multiply the density of workers by the relative lengths of the intervals, $1/(1-\gamma)$, to preserve the total mass. For convenience I also define $g(A_i, p) = 0$ for $p > 1$ to deal with the fact that in the third line the argument $p/(1-\gamma)$ can be greater than 1.

For each A_i , (13) holds on the interval $(\underline{p}(A_i), 1)$ except for p_0 . There are special flows at $\underline{p}(A_i), 1, p_0$. Workers separate to unemployment when their belief hits $\underline{p}(A_i)$. At $p = 1$, the match quality is high for sure and thus there is no more learning. All new matches start with a belief p_0 which generates an extra inflow into p_0 , and thus the density has a kink at p_0 .

For each A_i , the system (13) has two boundary conditions and one condition for p_0 . I state them explicitly in Appendix A.2, here I describe them in words. The boundary condition for $\underline{p}(A_i)$ requires that the density at $(A_i, \underline{p}(A_i))$ is zero: this is because as soon as the belief p hits the boundary, a match ends. The second boundary condition balances flows in and out from the firms with productivity A_i . Finally, the condition for p_0 equalizes the inflow into p_0 , which is on top of learning, to the inflow of newly formed matches.

The density of workers' beliefs determines the unemployment and employment rates, which determines the total number of searchers. Workers receive offers both when they are employed and unemployed, and thus they all determine the number of searchers. The two groups of workers receive offers at different rates and thus their masses are appropriately weighted. The mass of searchers S is given by

$$S = U + \psi E \quad (14)$$

$$E = 1 - U \quad (15)$$

$$U = 1 - \sum_{i=1}^I \int_0^1 g(A_i, p) dp \quad (16)$$

where U and E is the unemployment and employment rates, respectively.

3.8.2 Distribution of vacancies and the total number of vacancies

The pool of vacancies is heterogenous since vacancies are posted by firms with different productivity levels. To determine the distribution of vacancies one needs to know the share of firms with a given productivity level A_i and the vacancy posting decision $v(A_i)$ of these

firms. In a stationary equilibrium, the distribution of firms over the productivity levels is described by a vector $\bar{\omega}$ which satisfies $\bar{\omega}\Omega = \mathbf{0}$. Thus, the share of vacancies of type A_i on all posted vacancies is given by

$$\bar{v}_i = \frac{\bar{\omega}_i v(A_i)}{\sum_{j=1}^I \bar{\omega}_j v(A_j)}, \quad \forall i = 1, \dots, I, \quad (17)$$

where $\bar{\omega}_i$ are elements of $\bar{\omega}$.

Finally, the equilibrium distribution of productivities $\bar{\omega}$ determines the total number of posted vacancies V ,

$$V = \sum_{j=1}^I \bar{\omega}_j v(A_j). \quad (18)$$

3.8.3 Definition of the steady state equilibrium

A **steady state equilibrium** is a collection of the value functions $\{J(A_i, p), W(A_i, p), U\}$, wage function $w(A_i, p)$ for $(A_i, p) \in \mathcal{E}$, vacancy posting function $v(A_i)$, $\forall i$, distributions of vacancies and workers $\{\bar{v}_i, g(A_i, p)\}_{i=1}^I$ and the numbers $\{\theta, f, q\}$ such that:

1. Given $\{f, q, \bar{v}_i \forall i\}$, functions $J(A_i, p), W(A_i, p), U, w(A_i, p), v(A_i)$ solve (6), (8), (5), (12).
2. The distribution $g(A_i, p)$ solves (13) and is time-invariant.
3. The variables $\{f, q, \bar{v}_i \forall i\}$ solve (17) and (4) with total vacancies V and searchers S given by (18) and (14).

3.9 Characterization of the decision rules

In this section I characterize the decision rules of an employed worker and a firm. Notice that an unemployed worker does not make any active decision: in equilibrium, she accepts all offers she gets because unacceptable jobs will not be posted. The driving force of the model is worker's decision to separate from the current firm. A worker separates if she receives a better offer, or when she learns bad news either about the quality of her match or her firm. I describe this decision in more detail below. I start by stating the properties of the value function.

Lemma 1 *The value functions $W(A, p)$ and $J(A, p)$ are increasing in A and p , and convex in p .*

A higher productivity level A implies that a worker with a given belief p produces a higher output, which increases the surplus of the match. Both the worker and the firm capture some of this extra surplus and therefore the value of the match to them increases. An increase in p works in a similar fashion: a worker with a higher belief p in expectation produces a higher output, which again increases the surplus of the match.

Convexity of the value function is a standard result in Bayesian learning. As mentioned for example in Moscarini (2005), if the value function was linear, there would be no benefit from learning. The expected value of the match at time $t + dt$ would equal the value at time t , $E_t [W(A_i, p_{t+dt})] = W(A_i, p_t)$, and thus new information obtained at time t would not have brought any additional benefit. However, if the value function is convex, it holds that $E_t [W(A_i, p_{t+dt})] > W(A_i, p_t)$ which reflects the fact that a worker can make a more informed decision at time $t + dt$.

3.9.1 Separations to unemployment

An employed worker can, at any time, quit to unemployment. She may choose to exercise this option if she receives bad news about her match even if firm's productivity stays unchanged, or when she learns bad news about firm's productivity. The decision to quit to unemployment is described by a separation threshold. The return from quitting is U , and the return from staying in a firm with productivity level A_i and a belief p is $W(A_i, p)$. The worker stays in a job as long as $W(A_i, p) > U$ and quits if $W(A_i, p) < U$. Thus, for each A_i there exists a separation threshold $\underline{p}(A_i)$ defined as

$$U = W(A_i, \underline{p}(A_i)).$$

The worker quits if $p \leq \underline{p}(A_i)$, and stays otherwise.

Lemma 2 *Assume the value function $W(A, p)$ is increasing in p and A . Then the separation threshold $\underline{p}(A_i)$ is decreasing in A_i .*

Proof. See Appendix A.1. ■

This result implies that a worker is more willing to tolerate an unpromising match in a firm with a higher productivity level. Conditional on p , a higher productivity increases her surplus from the match while does not have any effect on the value of being unemployed. A firm is willing to keep her, because existing workers do not crowd out new hires due to linear production technology.

A worker can choose to separate even if the conditions in the firm have not changed. Workers continually update beliefs about their quality by observing output realizations. If lower than expected output is observed, the belief downgrades, and can reach the separation threshold $\underline{p}(A_i)$. In such a case, a worker becomes confident that her match quality is poor and rather quits to unemployment where she can search for better matches.

A change in firm's productivity may induce a worker to quit to unemployment. There are two forces in play: a new technology shock shifts the separation threshold $\underline{p}(A_i)$, and the technology-adoption shock decreases worker's belief that her match quality is high.

Due to the match-quality shocks, it is possible that a worker quits even after firm's productivity increases. This case stresses the idea that the technology is not fully disembodied from workers, and even a positive technology shock could make some workers less productive and induce them to quit to unemployment.

3.9.2 Separations to another job

A worker receives offers from other firms even while employed and decides whether to accept them or not. If she does, the match quality is drawn again from the distribution F_μ and her belief about the match quality is reset to p_0 . A worker tends to accept the outside offer when her prospects on the current job are bad, be it because of the match quality itself or firm's productivity, or when the offer comes from a firm with a sufficiently higher productivity. Worker's decision to accept an offer is described by a separation threshold which depends both on the current and contacting firm's productivity levels.

Consider a worker employed in a firm with productivity A_i with belief p who gets an outside offer from a firm with productivity A_j . Her value from staying with the current employer is $W(A_i, p)$ while the value from accepting an outside offer is $W(A_j, p_0)$. The optimal strategy is then to accept an offer if $W(A_j, p_0) > W(A_i, p)$ and reject otherwise. This defines a threshold $\bar{p}(A_i, A_j)$ for which

$$W(A_j, p_0) = W(A_i, \bar{p}(A_i, A_j))$$

such that a worker with a belief below the threshold, $p < \bar{p}(A_i, A_j)$, employed in a firm with productivity A_i accepts an offer from a firm with productivity A_j .

Lemma 3 *Assume the value function $W(A, p)$ is increasing in p and A . Then the separation threshold $\bar{p}(A_i, A_j)$ is decreasing in the current firm's productivity A_i and increasing in the contacting firm's productivity A_j .*

Proof. See Appendix A.1. ■

A worker accepts an outside offer when her current match looks unpromising enough and her belief is below a certain threshold. In low-productivity firms the separation threshold is high which implies that even workers with a relatively high confidence in their match quality are willing to accept outside offers. On the other hand, the separation threshold decreases with the productivity of the contacting implying that in order to take this offer, the worker must be very confident that her current match is poor.

3.9.3 Vacancy posting

A firm hires workers through posting vacancies which is costly. A firm posts vacancies up to the point where the marginal costs, $c\eta v^{\eta-1}$, equals the expected benefit from filling a vacancy, $qJ(A_i, p_0)$. The expected gain from a filled vacancy is increasing in firm's productivity level A_i and thus a more productive firm posts more vacancies.

Lemma 4 *Assume the value function $J(A, p)$ is increasing in p and A . Then the number of posted vacancies $v(A)$ is increasing in A .*

Proof. The FOC implies that $c\eta v(A)^{\eta-1} = qJ(A, p_0)$ for $v \geq 0$. Since $J(A, p_0)$ is increasing in A , so must be $v(A)$. ■

4 Calibration

In this section I parameterize the model to match certain characteristics of the Austrian labor market. The parameter values are summarized in Table D. The model is calibrated at the quarterly frequency.

I need to choose values for the time preference ρ , the vector of the firm-level productivity values A and its transition matrix Ω , the learning parameters $\sigma_x, \mu_H, \mu_L, p_0$, the flow value of unemployment b , the relative arrival rate of the offers for employed and unemployed ψ , the curvature in the vacancy posting function η , and the bargaining power of the worker β .

I do not need to calibrate the matching function and the level of the vacancy-posting cost function c if I choose a value for the job-finding rate f_u directly. The decision problems of a firm and a worker depend on the job-finding rate f_u . Even though firm's decision on how many vacancies to post depends on the parameter c , it enters worker's and firm's value functions only through the vacancy ratio.

Setting the value of the job-finding rate f_u even though it is an endogenous object is in this model innocuous: it is always possible to find a value of c which is consistent with the equilibrium value of the job-finding rate f_u .

The remaining parameters can be split into two broad groups, those which mainly affect the job flows and those that primarily drive the worker flows. The key statistic I will use to describe the job flows is the autocorrelation and standard deviation of the employment changes at the firm level, the relative response of the hiring and separation rates to a positive productivity shock, and the average level of the hiring rate. To calibrate the parameters governing the worker flows I use information on the hazard rate of separation at different tenures, and the transition rates between different jobs and unemployment.

I start with parameters governing the job flows. The primary driving force of the job flows at the firm level are the productivity shocks. I choose the Markov chain for the productivity process A to approximate an estimated AR(1) process for the dynamics of firm's employment. I estimate the equation

$$\log EMP_{e,t} = \rho \log EMP_{e,t-1} + \varepsilon_{e,t},$$

where $EMP_{e,t}$ is employment in firm e at time t , $|\rho| < 1$ and $\varepsilon_{e,t}$ is a white noise with variance σ_ε^2 . I find that the quarterly autocorrelation is $\rho = 0.96$ and the standard deviation is $\sigma_\varepsilon = 0.32$. I employ Rouwenhorst method as described in [Kopecky and Suen \(2010\)](#) to approximate this AR(1) process by a 5-state Markov process.

The values of the vector A pin down the scale of production. The exact location of the scale does not play a role: shifting the values of the vector A and of the flow value of unemployment b by a constant while keeping other parameters unchanged will not have an impact on equilibrium outcomes. I thus normalize the mean value of A to zero.

The volatility of the productivity process A is an important but not the only determinant of the firm-level employment volatility. The value of the match quality μ relative to the productivity levels A affects the extent to which a higher productivity shock A increases worker's expected output. This determines how many more vacancies a firm posts at different values of A as well as the change in willingness of a worker to separate, both of which affect the employment volatility at the firm level. I will set the value of μ to match the firm-level volatility of the log-employment. Again, the location of μ is not important: adding a constant to μ_H , μ_L and b will have no impact on equilibrium. I thus normalize $\mu_H = -\mu_L$.

I used the job flows at the firm level, i.e. the changes in the firm employment, to calibrate the process for the productivity. I will now utilize the decomposition of the employment changes into new hires and separations to calibrate the curvature of the vacancy posting

costs η . In response to a better productivity shock, a firm hires more workers. The increase in the number of newly hired workers is larger, the smaller the vacancy posting costs are (i.e. η is small), and the larger the increase in the productivity is. While decreasing the vacancy posting costs and increasing the productivity level has a similar effect on the hiring rate, it has a different effect on the separation rate. In particular, the separation rate is smaller if the increase in the productivity level is larger, but the vacancy posting costs have no direct effect on the separations. Therefore, the parameter η can be calibrated using the relative response of the hiring and separation rate to a new productivity shock. In the data, establishments which grow by 5% in response to a new productivity shock experience the hiring rate of 11.8% on average and a separation rate of 6.8%. In comparison, the establishments with zero growth rate experience a hiring and separation rate of 5%. In the calibration I will therefore target the hiring rate in establishments with 0 and 5% growth rate.

Finally, the level of the hiring rate is governed by the parameter p_0 , the proportion of the high matches in economy. A firm posts vacancies up to the point where the expected gain from filling a vacancy equals the marginal costs of posting a vacancy. The value of a newly hired worker depends on the probability p_0 that her match quality is high. A higher p_0 increases the value of a newly hired worker, which motivates firms to post more vacancies, thus increasing the hiring rate in the economy. I will set the value of p_0 to target the quarterly hiring rate of 9%.

The remaining parameters mostly affect worker flows.

Worker's decision to separate to unemployment depends mainly on the consumption flow b and the probability of finding a job f_u while unemployed. I set the parameter b to match the unemployment rate, which in Austria was 6.5% during the analyzed period. However, since there are only two labor market states in the model - employment and non-employment - while workers in the data can be employed, unemployed and out of labor force, I adjust the unemployment rate to include also workers out of the labor force. This gives me a non-employment rate of 8.4%.

The value of the job-finding rate can be estimated in two ways. First, the Poisson arrival of the offers implies that the average unemployment duration is $1/f_u$, which in Austria is 6.75 months or 2.25 quarters, meaning that $f_u = 0.45$. Second, I can directly measure the share of unemployed workers who find a job within any given month. The average of monthly job-finding rate in period 1986 – 2007 is 14.6% which implies the quarterly job-finding rate of 0.438. These two measures give very similar job-finding rates; I choose $f_u = 0.45$.

The employed workers are contacted by other firms at a different rate than unemployed

workers. To set the relative intensity of the contact rate, ψ , I use data on job-to-job transitions. Out of all workers who separate, one third starts a new job immediately without experiencing an unemployment spell. I will target this number in the calibration.

One of the key predictions of the model is a decreasing hazard rate of separation as a function of tenure. Its shape is governed by two parameters: σ_x and γ . The parameter γ mainly affects the hazard rate at high tenures. To understand the role of γ , consider a case without technology-adoption shocks, i.e. $\gamma = 0$. In such an environment, the workers who become confident enough that their match quality is high will never separate from a firm. Since on average the confidence about the high match quality is increasing in tenure, this implies that the high-tenure workers have a negligible hazard rate of separation. The technology-adoption shocks might turn the high-quality into low-quality matches, and thus they affect mostly workers with a strong belief that their match quality is high, which are long-tenure workers.

The steepness of the hazard rate curve is driven by the signal-noise ratio $(\mu_H - \mu_L) / \sigma_x$. For the given values of μ_H and μ_L , a higher σ_x increases the noise around the true μ , making learning slower and the hazard rate curve flatter. The rate at which the empirical hazard rate decays at short tenures (up to 5 quarters) is different from the rate at which it decays at longer tenures. The model however generates a smooth decay rate and thus will not be able to capture the change in the decay observed in the data. I choose to target the hazard rate of separation after 4 quarters. Since I already target the separation rate at long tenures, choosing the hazard rate at some early tenure will depict the decay. I choose the match the hazard rate of separation of 10% at the 5 quarters.

Finally, I set the discount rate $\rho = 0.0125$ which corresponds to the 5% annual interest rate. I impose symmetry in bargaining and set $\beta = 0.5$. Since I focus on the job and worker flows in this paper, the parameter β does not play a crucial role as it determines how the rents are split between a firm and a worker.

In the analytical part I normalized the labor force N and the mass of firms F to one, but in the simulation I will use $N = 5000$ and set the number of firms $F = 400$.

5 Results

In this section I first argue that the model developed in the previous sections is empirically relevant as it can several cross-sectional patterns observed in the data. I use the calibrated model to evaluate the importance of the different channels to the magnitude of the worker

flows.

I solve the model numerically and simulate it. The details of the numerical procedure and simulations are described in Appendix B.1 and B.2. I take one day as one period and run the economy for 10^8 periods. Using the simulated data, I construct quarterly time series for employment, hires, separations and tenure distribution for each firm, and repeat the analysis I did with the empirical data.

5.1 Cross-sectional distribution of worker and job flows

I first examine the predictions of the model for the cross-sectional distribution of worker and job flows. I use the simulated quarterly time series for the hiring, separation and employment growth rates. I sort firms into growth bins and calculate the employment-weighted hiring and separation rate for each bin. Figure 5 depicts the result. The pattern is consistent with the empirical job and worker flow dynamics. There is simultaneous hiring and separation across the whole range of the growth rates. The separation rate is increasing with the contraction rate in shrinking establishments, and it is growing with the growth rate in the growing establishments.

To understand the mechanism which generates the observed pattern between the growth rate and separations, consider a firm which has been in its steady state level of employment for some time and receives a better productivity shock. Upon arrival, the separation threshold $\underline{p}$ shifts down. This has an immediate impact on workers close to the separation threshold who instead of separating to unemployment are now more willing to tolerate a poor match. Through this channel the separation rate of the low-tenure workers decreases since, on average, workers with low p are those with short tenure.

The technology-adoption shocks affect workers with all beliefs p . The workers in a firm face a positive probability that they will not be able to implement the newly arrived technology, and thus become less valuable to the firm. This option alters their beliefs about the match quality. Workers update their belief downward which brings them closer to the separation threshold. Then, if lower than expected realizations of the output flow is observed, it is interpreted as a switch to the low match quality and these workers eventually reach the separation threshold and separate. This channel can have a significant effect on the separation rate. Due to selection, firms have a higher share of workers who are good matches, and thus the technology-adoption shocks effectively create low-quality matches which over time separate.

The mechanism is similar in firms which experienced an adverse productivity shocks.

The separation threshold shifts up inducing vulnerable workers with low belief p to separate immediately. This increases the separation rate of the low-tenured workers. The technology-adoption shock triggers workers who were believed to be of high quality as the quality of their match could have changed again.

The model predicts that the separation rate is increasing in the growth rate in the growing firms, due to two effects. First, the growing firms have a higher proportion of short-tenure workers who face the highest risk of being separated. Second, due to the technology-adoption shocks, an increase in the productivity level is associated with a higher risk of being separated also for workers with longer tenures. The fact that the hazard rate of separation in firms with positive growth is higher than in firms with zero growth across all tenures indicates that both of these mechanisms play a role.

The relationship between the hiring rate and the firm growth rate generated by the model is consistent with the data. The model predicts that the hiring rate is positive for the shrinking establishments, and it is positive and increasing with the growth rate in the growing establishments. The hiring policy in the model is very simple. The number of newly hired workers depends only on the current productivity level of the firm: the more productive firms hire more workers.

5.2 Worker flows between labor market states

The predictions of the model are consistent with the cross-sectional distribution of job and worker flows as measured by hiring and separation rates. I now investigate whether the model explains the worker flows between employment and unemployment and their link to the establishment growth. I again focus on decomposition of separations.

Figure 6 shows the decomposition of the separations in the simulated data.

Separations to other jobs account for a larger share of separations in the growing firms while their importance decreases in the shrinking establishments. Innovations to the firm-level productivity drive job flows, and at the same time, productivity determines the value of the current match relative to outside option. Because the decision to separate to unemployment can be taken immediately while searching for better job offers takes time, separations into unemployment will respond more strongly to the job growth. Indeed, as Figure 6 shows, in the shrinking firms the model predicts a stronger decay of the share of separations to employment than is observed in the data. Adding an endogenous search intensity to the model can resolve this difference, as workers in the shrinking firms would search for new employment opportunities at a higher rate, thus being contacted more frequently.

5.3 Hazard rate of separation at different tenures

The key prediction of the learning models is the decreasing relationship between the hazard rate of separation and worker's tenure. This is due to selection: workers who learn that their match quality is low separate and therefore among workers with long tenures there is a low share of workers whose match quality is low. As a result, the probability that a match ends decreases with tenure. The hazard rate can be increasing in the early phases.

Figure 7 shows the hazard rate of separation as predicted by the model. The hazard rate is increasing in early tenures, but soon starts to decline.

The hazard rate curve depends on the firm growth rate. Figure 8 depicts the hazard rate curve in firms with different growth rates and shows that the pattern is consistent with the data. Compared to the firms which do not grow, the hazard rate at all tenures is higher in firms with positive employment changes. This is a consequence of the technology-adoption shocks: a positive productivity shock induces some vulnerable workers (those with low p) to stay which tends to decrease the hazard rate for low-tenured workers, and has almost no impact on workers with long tenures. However, as some workers are not able to adopt the new technology, even workers with long tenures who were believed to have a high match quality are now more prone to separate.

The hazard rate of separation across tenures increases with the contraction rate. An adverse productivity shock induces some workers with lower tenures to leave, while the technology-adoption shock triggers workers with higher tenures. Both forces work in the same direction, and increase the hazard rate of separation for both short and long tenure workers.

The model thus rationalizes the observed dependence of the hazard rate curve on the establishment growth rate.

5.4 Decomposition of the separation rate

There are three separation channels in the model. A worker decides to separate when she learns bad news about her match quality, or about the firm, or when she receives a better offer from an outside firm. I decompose the separation rate according to these three motives to establish their importance.

I distinguish these channels in the following way. If a worker separates because her belief reaches the separation threshold $\underline{p}(\cdot)$, I assign the separation to the learning mechanism. If worker's separation is induced by a change in firm's productivity level, I assign the separation

to the second channel, and finally, I assign the job-to-job transitions to the worker receiving a better offer.

In the calibrated model, the quarterly separation rate is 5.6%. The share of workers who separate because they learn about their poor match quality is 3.12%. The learning is thus an important mechanism which accounts for more than half of all separations. The 1.95% of the workforce separates directly to another job, while 0.56% separates because a firm receives a new productivity shock. Uncertainty at the firm level thus account for a relatively small share of the separations.

I illustrate the contribution of these channels to the separation rate by shutting down each of the channels separately and running again the simulations. The results are reported in the Table 6. I shut down the firm-specific shocks by setting all values of A equal to the mean value of A , that is, $A_i = 0 \forall i$. This means that a firm receives new productivity shocks according to the intensity matrix Ω , but the values are the same. However, I keep this structure to ensure that the technology-adoption shocks arrive at the same rate as in the full model. I turn off the search on the job channel by simply setting the contact rate for the employed workers to zero, $\psi = 0$.

The first row in Table 6 reports the decomposition of the separation rate in the full model. The second line corresponds to a model with no firm-specific shocks and no search on the job, and thus all separations can be attributed to the learning mechanism. The separation rate is 3.74% as compared to 5.62% in the full model, again showing that the learning mechanism accounts for most of the separations. Once the search on the job is included into the model, the separation rate increases to 4.59%, while around one third of these workers separate due to accepting an offer from an outside firm. Finally, the last row shows a version of the model with learning and firm-level productivity shocks. The separations which can be attributed to the uncertainty at the firm level is constitute around 20% of all separations, while the learning mechanism accounts for the remaining 80%.

6 Conclusion

I study the joint behavior of the job and worker flows in an equilibrium model with distinct roles for shocks at the firm level and the level of individual matches between a worker and a firm. I provide empirical evidence that both types of shocks are important determinants of the labor market flows. The model incorporates the learning about the match quality mechanism into the search and matching framework. I extend the framework to multi-worker

firms which thus allows me to disentangle job and worker flows.

I calibrate the model to the aggregate statistics of the Austrian labor market and show that the model generates dynamics which is consistent with the observed cross-sectional distribution of the job and worker flows. I use the calibrated model to evaluate the contribution of different shocks to the worker flows. I find that the learning mechanism accounts for more than half of all separations, which suggests that the idiosyncratic shocks at the worker level play an important role in explaining the large magnitude of the worker flows.

References

- Altonji, Joseph G., and Charles R. Pierret, 2001. "Employer Learning and Statistical Discrimination." *The Quarterly Journal of Economics*. 116 (1): 313–350.
- Belzil, Christian, 2000. "Job Creation and Job Destruction, Worker Reallocation, and Wages." *Journal of Labor Economics*. 18 (2): 183–203.
- Bloom, Nicholas, 2009. "The Impact of Uncertainty Shocks." *Econometrica*. 77 (3): 623–685.
- Burdett, Kenneth, 1978. "A Theory of Employee Job Search and Quit Rates." *The American Economic Review*. 68 (1): 212–220.
- Burdett, Kenneth, and Dale T. Mortensen, 1998. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review*. 39 (2): 257–273.
- Burgess, Simon, and Helene Turon, 2010. "Worker flows, job flows and unemployment in a matching model." *European Economic Review*. 54: 393–408.
- Davis, Steven J., Jason Faberman, and John Haltiwanger, 2006. "The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links." *Journal of Economics Perspectives*. 20 (3): 3–26.
- Davis, Steven J., R. Jason Faberman, and John Haltiwanger, 2011. "Labor Market Flows in the Cross Section and Over Time." .
- Davis, Steven J., John Haltiwanger, Ron Jarmin, and Javier Miranda, 2006. "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms." .
- Davis, Steven J., John C. Haltiwanger, and Scott Schuh, 1998. *Job Creation and Destruction*, The MIT Press, Cambridge, Massachusetts, first paperback edition edn.
- Faberman, R. Jason, and Eva Nagypal, 2008. "Quits, Worker Recruitment, and Firm Growth: Theory and Evidence." Federal Reserve Bank of Philadelphia Working Paper No. 08-13.
- Garibaldi, Pietro, and Espen R. Moen, 2010. "Competitive on-the-job search." .
- Gorry, Aspen, 2011. "Experience and Worker Flows." .
- Jovanovic, Boyan, 1979. "Job Matching and the Theory of Turnover." *Journal of Political Economy*. 87 (5): 972–990.
- Jovanovic, Boyan, and Robert Moffitt, 1990. "An Estimate of a Sectoral Model of Labor Mobility." *Journal of Political Economy*. 98 (4): 827–852.

- Kaas, Leo, and Philipp Kircher, 2010. “Efficient Firm Dynamics in a Frictional Labor Market.” .
- Kopecky, Karen A., and Richard M.H. Suen, 2010. “Finite state Markov-chain approximations to highly persistent processes.” *Review of Economic Dynamics*. 13: 701–714.
- Lange, Fabian, 2007. “The Speed of Employer Learning.” *Journal of Labor Economics*. 25 (1).
- Moscarini, Guiseppe, 2003. “Skill and Luck in the Theory of Turnover.” .
- Moscarini, Guiseppe, 2005. “Job Matching and the Wage Distribution.” *Econometrica*. 73 (2): 481–516.
- Nagypal, Eva, 2005. “On the extent of job-to-job transitions.” .
- Nagypal, Eva, 2007. “Learning by Doing vs. Learning About Match Quality: Can We Tell Them Apart?.” *Review of Economic Studies*. 74: 537–566.
- Pissarides, Christopher A., 2000. *Equilibrium Unemployment Theory*, The MIT Press, Cambridge, Massachussets, second edn.
- Postel-Vinay, Fabien, and Helene Turon, 2010. “On-the-Job Search, Productivity Shocks and the Individual Earnings Process.” *International Economic Review*. 51 (3): 599–629.
- Pries, Michael, and Richard Rogerson, 2005. “Hiring Policies, Labor Market Institutions, and Labor Market Flows.” *The Journal of Political Economy*. 113 (4): 811–839.
- Schnalzenberger, Mario, and Rudolf Winter-Ebmer, 2009. “Layoff Tax and Employment of the Elderly.” *Labour Economics*. 16: 618–624.
- Shimer, Robert, 2006. “On-the-job search and strategic bargaining.” *European Economic Review*. 50: 811–830.
- Shimer, Robert, 2010. *Labor Market and Business Cycles*, Princeton University Press.
- Stokey, Nancy L., 2008. *The Economics of Inaction*, Princeton University Press.
- Stokey, Nancy L., Robert E. Jr. Lucas, and Edward C. Prescott, 1989. *Recursive Methods in Economic Dynamics*, Harvard University Press.
- Wonham, W. Murray, 1964. “Some Applications of Stochastic Differential Equations to Optimal Nonlinear Filtering.” *SIAM Journal on Control and Optimization*. 2 (3): 347–369.
- Zweimuller, Josef, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf, and Simon Buchi, 2009. “Austrian Social Security Database.” .

A Omitted proofs and derivations

A.1 Properties of the separation thresholds

Assume that $W(A, p)$ is increasing in A and p . Then the separation threshold $\underline{p}(A_i)$ is decreasing in A_i . For $A_j > A_i$ we have

$$\begin{aligned} W(A_j, \underline{p}(A_i)) &> W(A_i, \underline{p}(A_i)) = 0 \Rightarrow \\ W(A_j, \underline{p}(A_i)) &> 0 = W(A_j, \underline{p}(A_j)) \Rightarrow \underline{p}(A_i) > \underline{p}(A_j). \end{aligned}$$

The separation threshold $\bar{p}(A_i, A_j)$ is decreasing in A_i . Consider $A_k > A_i$. Then,

$$\begin{aligned} W(A_j, p_0) &= W(A_i, \bar{p}(A_i, A_j)) < W(A_k, \bar{p}(A_i, A_j)) \\ W(A_j, p_0) &= W(A_k, \bar{p}(A_k, A_j)) < W(A_k, \bar{p}(A_i, A_j)) \Rightarrow \bar{p}(A_k, A_j) < \bar{p}(A_i, A_j) \end{aligned}$$

and therefore it is decreasing in A_i .

Assume that $W(A, p)$ is increasing in A and p . Then the separation threshold $\bar{p}(A_i, A_j)$ is increasing in A_j . Consider $A_l > A_j$. Then,

$$\begin{aligned} W(A_i, \bar{p}(A_i, A_j)) &= W(A_j, p_0) < W(A_l, p_0) = W(A_i, \bar{p}(A_i, A_l)) \\ &\Rightarrow \bar{p}(A_i, A_j) < \bar{p}(A_i, A_l) \end{aligned}$$

and thus it is increasing in A_j .

A.2 Distribution of (A, p)

To simplify the exposition, I define the following notation:

- 1) $\underline{p}_i = \underline{p}(A_i)$ the separation threshold to unemployment
- 2) $\bar{p}_{ij} \equiv \bar{p}(A_i, A_j)$, the separation threshold to other job
- 3) threshold L_{ji} defined as

$$L_{ji} = \max \left[\underline{p}(A_i), \frac{\underline{p}(A_j)}{1 - \gamma} \right].$$

The evolution of the joint distribution of beliefs and firms' productivity levels is described by the Kolmogorov forward equation. Imposing that the distribution is time-invariant, we

get

$$\begin{aligned} \frac{d}{dt}g(A_i, p, t) = 0 &= \frac{d^2}{dp^2} \left[\frac{1}{2} \sigma_p^2(p) g(A_i, p) \right] \\ &- \left[f_e \sum_{\{j: W(A_i, p) < W(A_j, p_0)\}} \bar{v}_j + \sum_{j \neq i} \omega_{ij} \right] g(A_i, p) \\ &+ \sum_{j \neq i} \omega_{ji} \frac{g\left(A_j, \frac{p}{1-\gamma}\right)}{(1-\gamma)} \end{aligned}$$

with two boundary conditions and one condition for p_0 :

1. for all i , there is no mass at the separation-to-unemployment threshold:

$$g(A_i, \underline{p}(A_i)) = 0 \quad (19)$$

2. for all i , inflow into firms of with productivity A_i must equal the outflow from firms of with productivity A_i :

$$\begin{aligned} inflow_i &= outflow_i \quad (20) \\ inflow_i &= f_u \bar{v}_i \left[1 - \sum_j \int_0^1 g(A_j, p) dp \right] + f_e \bar{v}_i \sum_{j \neq i} \int_0^{\bar{p}_{ji}} g(A_j, p) dp \\ &+ \sum_{j \neq i} \omega_{ji} \int_{L_{ji}}^1 g(A_j, p) dp \\ outflow_i &= \frac{1}{2} \sigma_p^2(\underline{p}_i) g'(A_i, \underline{p}_i +) \\ &+ f_e \sum_{j \neq i} \bar{v}_j \int_0^{p_{ij}} g(A_i, p) dp + \sum_{j \neq i} \omega_{ij} \left(\int_{\underline{p}_i}^1 g(A_i, p) dp \right) \end{aligned}$$

where $g'(A_i, \underline{p}_i +)$ is the derivative from the right with respect to p . The three terms in *inflow* measure the mass of workers who come from unemployment, from other firms through on the job search, and from firms which received productivity A_i , respectively. The four terms in *outflow* measure the mass of workers who leave due to endogenous separations, accepting an offer from firms of different type (search on the job), and due to firms receiving a new productivity draw A_j . One can verify that summing (20) through all i results in a condition that total flows in and out of unemployment must

be equalized:

$$f_u \left[1 - \sum_i \int_0^1 g(A_i, p) dp \right] = \sum_i \frac{1}{2} \sigma_p^2 (\underline{p}(A_i)) g'(A_i, \underline{p}(A_i)) + \sum_i \sum_{j \neq i} \omega_{ji} \int_0^{L_{ji}} g(A_j, p) dp$$

The left-hand side is the unemployment outflow. The unemployment inflow consists of two terms, the first one measures the mass of workers who separate to unemployment due to hitting the separation threshold. The second terms corresponds to workers who separate due to change in the separation threshold after a firm receives a new productivity shock.

3. for all i , the mass of workers at $p = p_0$ on top of those who are there due to learning must be the inflow from unemployment and search on the job

$$\begin{aligned} & \frac{1}{2} \sigma_p^2 (p_0) [g'(A_i, p_0-) - g'(A_i, p_0+)] = \\ & f \bar{v}_i \left[1 - \sum_j \int_{\underline{p}(A_j)}^1 g(A_j, p) dp \right] + \psi f \bar{v}_i \sum_{j \neq i} \int_{\underline{p}(A_j)}^{\bar{p}_{ji}} g(A_j, p) dp \end{aligned} \quad (21)$$

The first line measures the inflow into p_0 which is not due to learning. The second line is the inflow from unemployment and the search on the job.

A.3 The system of ODEs for the value function $J(A_i, p)$

I will derive a system of ODEs for the vector of value functions $J(A_i, p)$, $i = 1, \dots, I$. My goal is to manipulate value function (8) so that it only depends on the vector $J(A_i, p)$, $i = 1, \dots, I$, endogenous object $f, \bar{v}_i, \underline{p}_i, \bar{p}_{ij}, \forall i, j$, and the parameters of the model.

First notice that the surplus sharing rule (10) implies that

$$W(A_j, p_0) - W(A_i, p) > 0 \iff J(A_j, p_0) - J(A_i, p) > 0, \forall i, j, p,$$

and therefore one can rewrite the indicator function in the equation (8) using values of $J(A_i, p)$ only.

Second, I find an expression for wage. I substitute out the value function (8) and (6), to find

$$w(A_i, p) = (1 - \beta) \rho U + \beta \left(\bar{\mu}(A_i, p) - f_e \sum_{j=1}^N \bar{v}_j \mathbf{I}_{J(A_j, p_0) - J(A_i, p) > 0} J(A_j, p_0) \right). \quad (22)$$

From this equation, I need to eliminate the value of unemployment U using (10) to rewrite the value of being unemployed (5) as

$$\rho U = b + f \sum_{j=1}^N \bar{v}_j \frac{\beta}{1-\beta} J(A_j, p_0),$$

and find an expression for the wage,

$$w(A_i, p) = (1-\beta)b + \beta \bar{\mu}(A_i, p) + \beta f \sum_{j=1}^N \bar{v}_j (1 - \psi \mathbf{I}_{J(A_j, p_0) - J(A_i, p) > 0}) J(A_j, p_0).$$

Finally, by plugging this into the value function (8), I find a system of ODEs for the vector of $J(A_i, p)$

$$\begin{aligned} (\rho + \delta) J(A_i, p) = & (1-\beta)(\bar{\mu}(A_i, p) - b) + \sigma_p(p) \frac{\partial^2 J(A_i, p)}{\partial p^2} + \\ & -\beta f \sum_{j=1}^N \bar{v}_j (1 - \psi \mathbf{I}_{J(A_j, p_0) - J(A_i, p) > 0}) J(A_j, p_0) \\ & -\psi f \sum_j \bar{v}_j \mathbf{I}_{J(A_j, p_0) - J(A_i, p) > 0} J(A_i, p) \\ & + \sum_{j \neq i} \omega_{ij} (J(A_j, p'_{ij}) - J(A_i, p)) \end{aligned} \quad (23)$$

which holds for all $(A_i, p) \in \mathcal{E} \setminus \{(A_i, \underline{p}(A_i)), (A_i, 1)\}$.

There are three sets of conditions for the system:

1. value-matching

$$J(A_i, \underline{p}(A_i)) = 0 \quad \forall i = 1, \dots, I \quad (24)$$

2. smooth-pasting

$$\frac{\partial}{\partial p} J(A_i, \underline{p}(A_i)) = 0 \quad \forall i = 1, \dots, I \quad (25)$$

3. at $p = 1$, the second-order term in the ODE (23) drops out because $\sigma_p(1) = 0$, which

gives a condition

$$\begin{aligned}
\rho J(A_i, 1) &= (1 - \beta) (\bar{\mu}(A_i, 1) - b) + \\
&\quad - \beta \sum_j \bar{v}_j (f_u - f_e \mathbf{I}_{J(A_j, p_0) - J(A_i, 1) > 0}) J(A_j, p_0) \\
&\quad - f_e \sum_j \bar{v}_j \mathbf{I}_{J(A_j, p_0) - J(A_i, 1) > 0} J(A_i, 1) \\
&\quad + \sum_{j \neq i} \omega_{ij} (J(A_j, 1 - \gamma_{ij}) - J(A_i, 1)), \quad \forall i = 1, \dots, I
\end{aligned} \tag{26}$$

B Numerical procedure and simulations

B.1 Numerical procedure

I solve the system numerically. I create a grid for p , call it $\{p_k\}_{k=1}^K$ and discretize the system together with the boundary conditions.

For the known values of the separation thresholds and the distribution of vacancies $\{\underline{p}(A_i), \bar{p}(A_i, A_j), \bar{v}_i\}_{i=1}^I$, the discretized equations constitute a system of linear equations in unknowns $\{J(A_i, p_k)\}_{i=1, \dots, I, k=1, \dots, K}$. However, the values of $\{\underline{p}(A_i), \bar{p}(A_i, A_j), \bar{v}_i\}_{i=1}^I$ are determined endogenously within the system. I therefore proceed as follows:

Step 1: I guess values for $\bar{v}_i, \forall i = 1, \dots, I$.

Step 2: I guess values for $\underline{p}(A_i), \forall i = 1, \dots, I$.

Step 3: I guess values for $\bar{p}(A_i, A_j), \forall i, j = 1, \dots, I$.

Step 4: I solve the discretized system for the guessed values of $\{\underline{p}(A_i), \bar{p}(A_i, A_j), \bar{v}_i\}_{i,j=1}^I$.

Step 5: I verify whether the guess for $\bar{p}(A_i, A_j)$ is precise enough by checking the condition

$$J(A_i, \bar{p}(A_i, A_j)) = J(A_j, p_0), \quad \forall i, j.$$

If not, I update the guess for $\bar{p}(A_i, A_j)$ and repeat the steps 4 - 5 until the given precision criterium is met.

Step 6: I verify whether the guess for $\underline{p}(A_i)$ is precise enough by checking whether the smooth-pasting conditions (25) are satisfied. If not, update the guess for $\underline{p}(A_i)$ and repeat the steps 3-6 until the precision criterium for $\underline{p}(A_i)$ is met.

Step 7: I verify whether firms' decisions on posting vacancies is consistent with the guess

for $\{\bar{v}_i\}_{i=1}^N$ by checking whether the condition (27) holds (derived below):

$$\bar{v}_i = \frac{\bar{\omega}_i J(A_i, p_0)^{1/(\eta-1)}}{\sum_j \bar{\omega}_j J(A_j, p_0)^{1/(\eta-1)}}. \quad (27)$$

If not, I update the guess on $\bar{v}_i$ and repeat the steps 2-7.

The condition for the distribution of vacancies (27) is given by the decision of an individual firm on how many vacancies to post and the share of these firms in equilibrium. A firm of type A_i posts $v(A_i)$ vacancies such that the marginal costs of posting vacancies equals expected benefit from filling a vacancy:

$$\begin{aligned} C'(v) &= \kappa \eta v^{\eta-1} = q J(A_i, p_0) \\ v(A_i) &= \left(\frac{q}{\kappa \eta} J(A_i, p_0) \right)^{1/(\eta-1)} \end{aligned}$$

In a stationary equilibrium, the share of firms with productivity A_i is $\bar{\omega}_i$ where $\bar{\omega}_i$ is the i -th element of $\bar{\omega}$ solving $\bar{\omega} \Omega = \mathbf{0}$. The share of firms together with the number of vacancies give us the expression for the distribution of vacancies:

$$\begin{aligned} \bar{v}_i &= \frac{\bar{\omega}_i v(A_i)}{\sum_j \bar{\omega}_j v(A_j)} = \frac{\bar{\omega}_i \left(\frac{q}{\kappa \eta} J(A_i, p_0) \right)^{1/(\eta-1)}}{\sum_j \bar{\omega}_j \left(\frac{q}{\kappa \eta} J(A_j, p_0) \right)^{1/(\eta-1)}} \\ &= \frac{\bar{\omega}_i J(A_i, p_0)^{1/(\eta-1)}}{\sum_j \bar{\omega}_j J(A_j, p_0)^{1/(\eta-1)}}. \end{aligned}$$

B.2 Simulations

I simulate the model 10^8 times with one period being on day. I start from the steady state level of employment. Each employed worker draws her value of μ and is assigned to a firm of type A respecting the stationary distribution $\bar{\omega}_i$. From here, I run the economy forward.

The timing of events within one period is as follows:

1. production takes place
2. agents update beliefs based on the output realization
3. separations take place: i) endogenously if $p < \underline{p}(A_i)$, ii) via search on the job if $p < \underline{p}(A_i, A_j)$

4. hiring takes place: employed workers who accepted an outside offer and unemployed workers who got an offer join firms
5. measurement takes place: I measure hires, separations, employment, tenure distribution in each firm
6. firm receives a new productivity shock A_j , agents update beliefs to p' and a share γ of workers in these firms change the value of the match quality

I throw away first 10000 periods of the data. With the rest, I repeat the analysis I did with the empirical data.

C Data

C.1 General description

I use Austrian Social Security Database (ASSD) for the empirical analysis. The ASSD records the spells of individuals that contribute to the determination of eligibility and amount of the social security, sickness, health and accident benefits. These spells are then translated into the labor market status. I distinguish 4 statuses: employed, unemployed, maternity leave and retirement. The spells that are not relevant for the labor market status determination, like for example widower or foster-care benefits, are deleted from the database.

The ASSD is thus a dataset containing labor market histories of almost all individuals in Austria from 1972 to 2007 with observed spells of employment, unemployment, maternity leave and retirement. For each spell I observe its begin and end date. For employed individuals I observe an establishment code of the employer and annual earnings associated with this employer. If a worker holds multiple jobs within the same year, I see earnings from each job separately.

The database contains several demographic characteristics namely the year of birth, gender, nationality and region of residence. Education is provided by Public Employment Service Austria (AMS) and therefore is available only for those who went through at least one unemployment spell, which is around 35% of individuals in the sample. The annual income is bottom and top coded. I observe a 4-digit NACE industry code (Classification of economic activities in the European community) as well as a region of residence for the establishments.

Even though the ASSD covers the vast majority of the Austrian workers since 1972, there are some groups of workers who used to be exempt from paying the social security contributions, and thus would not be covered in the database since its beginning. These are the government employees who were added into the dataset only in 1988, the free contractual workers who were added in 1996, and the marginal part-time employees working less than 10 hours a week who were added in 1994. I exclude all three groups from my analysis. I consider only private full-time employees which eliminates and thus I exclude first two categories. To keep the sample consistent over time, I exclude the free contractual workers as well, which is only a small share of workers. According to the Austrian Labor Force Survey, the share of the free contractual workers is constant at around 1.5% of employment.

The dataset underreports unemployment spells for years before 1985 and therefore I focus only on a subsample of years 1986-2007.

C.2 Construction of the main variables

I use the establishment identification code to merge workers into establishments. For each establishment we construct quarterly time series of employment, hires and separations using the begin and end date of workers' employment spell. I say that a worker is employed in establishment e in quarter 1, 2, 3 or 4 of the given year if she works in the establishment e on the reference day March 31, June 30, September 30 and December 31 of the given year, respectively. In particular, this means that her spell started at or before and ended at or after the reference day. I consider a worker to be a hire in quarter i of the given year if the begin date of her employment spell falls between two reference dates i and $i - 1$ of that year. Separations are defined in the similar way: a worker is counted as a separation in quarter i if the end date of her spell falls between i and $i - 1$.

For each establishment e , I construct quarterly time series of employed, hired and separated workers, E_{et} , H_{et} , S_{et} . I use them to construct an establishment growth g_{et} , hiring h_{et} and separation s_{et} rates as

$$g_{et} = \frac{\hat{E}_{et} - E_{et-1}}{\frac{1}{2}(E_{et-1} + \hat{E}_{et})}, \quad h_{et} = \frac{H_{et}}{\frac{1}{2}(E_{et-1} + \hat{E}_{et})}, \quad s_{et} = \frac{S_{et}}{\frac{1}{2}(E_{et-1} + \hat{E}_{et})}$$

where $\hat{E}_{et} = E_{e,t-1} + H_{et} - S_{et}$ is a revised measure of employment which ensures that hiring,

separation and employment growths are consistent,

$$g_{et} = h_{et} - s_{et}. \quad (28)$$

Note that without the revised measure of employment, (28) does not hold. The reason is that workers who separate from their employers exactly on the reference date are counted as separations at time t but also as being employed at time t and thus violating the equation $E_{et} = E_{e,t-1} + H_{et} - S_{et}$.

I define the previous and subsequent labor market status for each employment spell of the workers. I say that the subsequent labor market state is employment if the worker starts a new employment spell within 28 days since the end of the considered employment spell. If she does not, then I define her subsequent spell to be unemployment if she starts an unemployment spell within a 28-day interval. Maternity and retirement spells are defined in a similar way, that such a spell starts within a 28-day interval. It is possible that no spell is recorded within the 28-day interval, in this case I define a worker to be out of labor force. I define the previous spell in a similar way. If a worker has been employed within a 28-day interval before her current employment has started, I consider her previous spell to be employment. If not, then I consider her previous spell to be unemployment there is a record within 28 days prior to the begin date. Analogously for maternity and retirement spells.

C.3 Tenure and hazard rate of separation

I define tenure of an employee at time t as the difference between the reference date t and the begin date of worker's spell. I measure tenure in quarters. Using the tenure, I construct a quarterly time series of tenure distribution for each establishment. Then the quarterly hazard rate of separation at tenure τ at time t is defined as the share of worker who had tenure τ at time $t - 1$ and separated during quarter i ,

$$HR_{\tau,t} = \frac{EMP_{\tau+1,t} - EMP_{\tau,t-1}}{EMP_{\tau,t-1}}. \quad (29)$$

I first pool data from all establishments together and apply the formula above to calculate the aggregate quarterly hazard rate of separation at tenures $\tau = 1, \dots, 40$ quarters, see Figure 2. The hazard rate starts at about 23% and declines to around 3% when the tenure is 10 years or more.

To examine how hazard rates depend on the establishment growth rate, I split the establishments into 6 growth bins, pool the data within each bin together and use (29) to construct the hazard rate curve for each of them. I use the following growth bins: $[-2, 0.2]$, $(-0.2, 0.05]$, $(-0.05, 0]$, $[0, 0.05]$, $(0.05, 0.2]$, $[0.2, 2]$. I use an increasing length of intervals because the number of establishment with a given growth rate declines quickly as one moves away from 0. Figure 3 displays the results. For each value of the growth rate, the hazard rate is decreasing in tenure as it was the case in the aggregate figure. The hazard rate curve depends on the growth rate. The entire hazard rate curve shifts up with the contraction rate in the shrinking establishments and with growth rate in the growing establishments.

C.4 Sample selection

I consider only full-time workers with employment spells of at least 14 days. I merge these workers into establishments as described above and construct quarterly time series for employment, hires and separations. I select establishments which in at least one quarter during their lifetime had more than 5 employees.

This gives me a sample of 2460 thousands employees and 112 thousand establishments in each quarter.

D Tables and figures

industry	<i>JC</i>	<i>JD</i>
agriculture	14.2	15.1
mining	4.2	6.1
manufacturing, non-durable	2.8	3.4
manufacturing, durable	2.9	3.2
utilities	1.1	1.7
construction	9.1	9.4
wholesale trade	3.5	3.7
retail trade	3.8	3.9
accommodation and food services	12.2	12.2
transportation	5.3	5.2
finance and business services	4.0	3.5
government, health care, education, church, arts	2.9	2.6
other services	4.5	4.8

Table 1: Job flows by industry, average quarterly rates 1986 - 2007. Source: Austrian social security data. The table shows the quarterly average job creation and destruction rates for different industries over the period 1986 –2007.

percentile	JC	JD
1%	0.21	0.27
5%	0.64	0.57
10%	0.94	0.82
25%	1.65	1.59
50%	2.91	2.87
75%	4.91	4.78
90%	8.97	9.41
95%	16.13	13.58
99%	24.83	33.84

Table 2: Distribution of the job creation and destruction rates. Source: Austrian social security data. The table shows the distribution of the average quarterly job creation and destruction rates for the 4-digit industries. The figures are employment-weighted.

	all	employment	unemployment	maternity	LF entrants	retirement
Hiring rate	9.35	2.45	2.42	0.1	1.15	–
Separation rate	9.02	2.41	2.57	0.1	–	0.38

Table 3: Decomposition of the hiring and separation rate according to the previous and subsequent labor market status. Source: Austrian Social Security Database. The table shows the average quarterly hiring and separation rates over the period 1986–2007.

Name	Description	Value
Calibrated parameters		
b	value of leisure	-2
σ_x	output noise	55
$\mu_H = -\mu_L$	high match quality	5
ψ	relative search intensity of employed and unemployed	0.17
p_0	initial belief	0.6
γ	μ -switching probability	0.25
η	curvature of vacancy costs	2
$\mathbf{A} = [A_1, \dots, A_I]$	vector of firm-specific shocks	$[-2.5, 2.5]$
$\Omega = \{\omega_{ij}\}_{i,j=1}^N$	transition matrix for $\mathbf{A}$	$\rho = 0.97$
Normalizations		
N	labor force	4000
F	mass of firms	200
Estimated parameters		
f	job-finding rate	0.45
Assigned parameters		
ρ	time preference	0.0125
β	bargaining power of the worker	0.5

Table 4: Parameters of the model and their values.

Empirical moment	Target	Model
unemployment rate	8.4%	8.2%
HR of separation at $\tau = 5$	10%	10%
HR of separation at $\tau = 40$	3.3%	3.1%
share of separations to other job	0.33	0.31
hiring rate, as share of employment	8.0%	5.6%
hiring rate of firms with 0% growth	5.1%	3.8%
hiring rate of firms with 5% growth	11.8%	10.8%
autocorrelation of log-employment	0.96	0.97
standard deviation of log-employment	0.35	0.36

Table 5: Empirical moments targeted in the calibration.

separations	all	learning	change in A	search OTJ
full model	5.62	3.12	0.56	1.95
w/o firm-specific shocks and OTJ search	3.74	3.74	0.00	0.00
w/o firm-specific shocks	4.59	3.14	0.00	1.45
w/o OTJ search	4.63	3.76	0.87	0.00

Table 6: Decomposition of the separation rate according to the source of separation. The Table shows the separation rates in the model decomposed according to its driving force. "Learning" stands for workers who separate due to hitting the separation threshold, "change in A " represents workers who separate due to the firm receiving a new productivity shock, and "OTJ search" corresponds to workers separating due to accepting an outside offer. The first row of the table corresponds to the full model, the other rows to the models where some of the above-mentioned channels had been shut down.

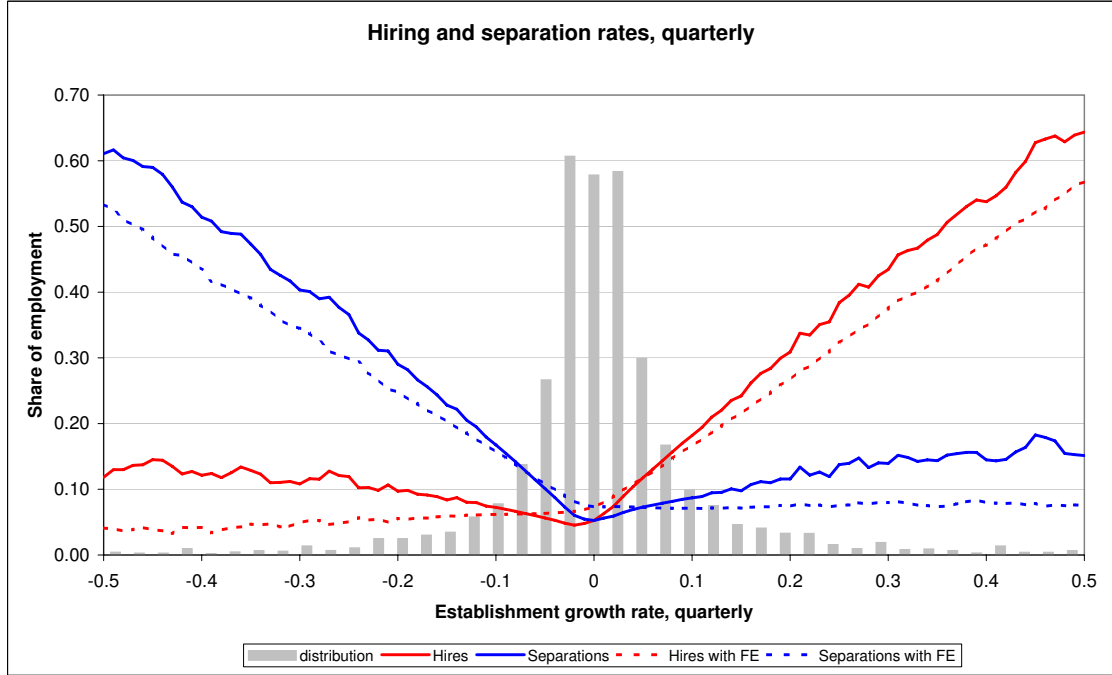


Figure 1: Hiring and separation rate as a function of firm growth rate. Source: Austrian social security data. I follow the [Davis, Haltiwanger, and Schuh \(1998\)](#) methodology and define the growth rate of an establishment e at time t as $g_{et} = (E_{e,t} - E_{e,t-1}) / Z_{et}$, where $E_{e,t}$ is the number of employees and $Z_{et} = 0.5 (E_{e,t} + E_{e,t-1})$ is the measure of the employer size. I similarly define measures of establishment-level hiring and separation rates to be $h_{et} = H_{et} / Z_{et}$ and $s_{et} = S_{et} / Z_{et}$ where H_{et} and S_{et} is the number of hired and separated workers in establishment e at time t . I control for the establishment fixed effects. The gray bars indicate the distribution of employment across growth-rate bins.

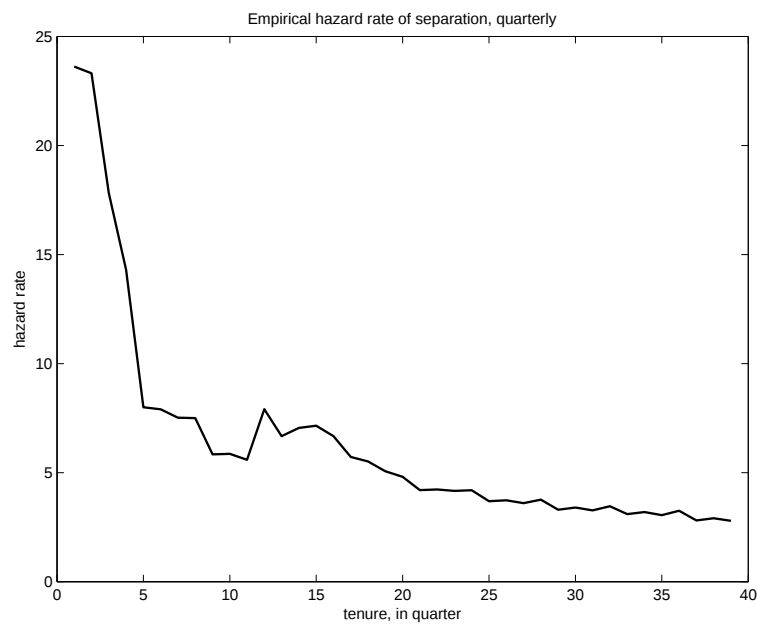


Figure 2: Hazard rate of separation. Source: Austrian social security data. The figure shows the quarterly hazard rate of separation as a function of tenure, measured in quarters. The hazard rate is estimated using completed spells only, using a linear probability model.

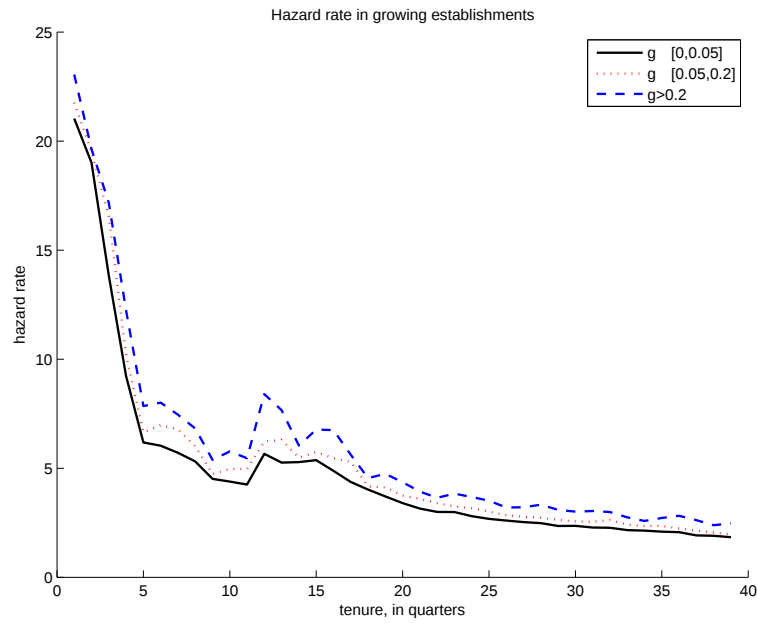


Figure 3: Hazard rate of separation in growing firms. Source: Austrian social security data. The figure shows the quarterly hazard rate of separation as a function of tenure, measured in quarters. For each value of the establishment growth rate, the hazard rate is calculated as a share of workers who separate at the given tenure relative to all workers at given tenure in firms with the given growth rate.

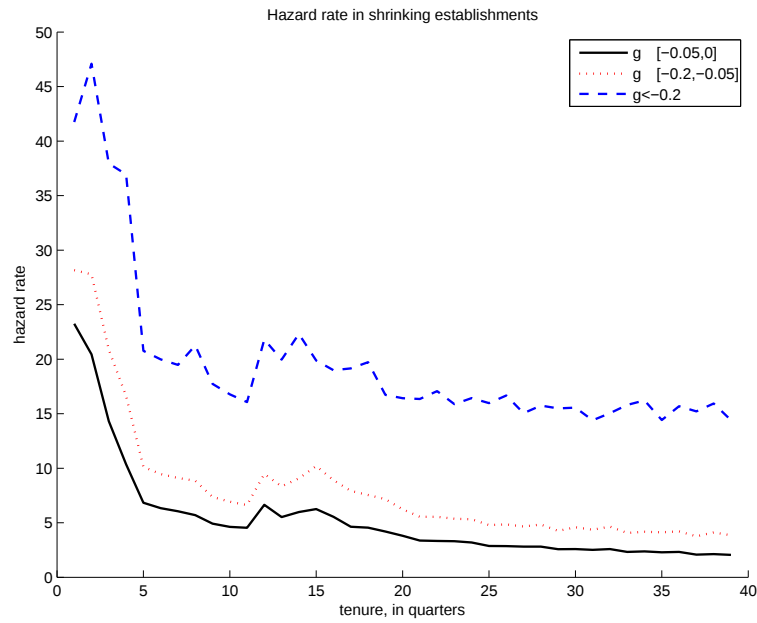


Figure 4: Empirical hazard rate of separation in shrinking firms. Source: Austrian social security data. The figure shows the quarterly hazard rate of separation as a function of tenure, measured in quarters. For each value of the establishment growth rate, the hazard rate is calculated as a share of workers who separate at the given tenure relative to all workers at given tenure in firms with the given growth rate.

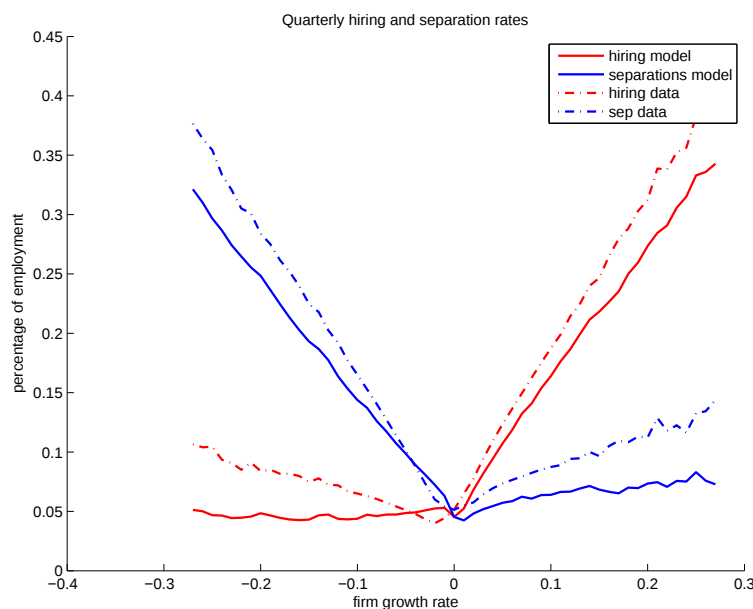


Figure 5: Hiring and separation rates as a function of firm growth rate. Model simulation. The figure shows the hiring and separation rates at firms with different growth rates using the simulated data. The dotted lines correspond to the data, the solid lines to simulated data.

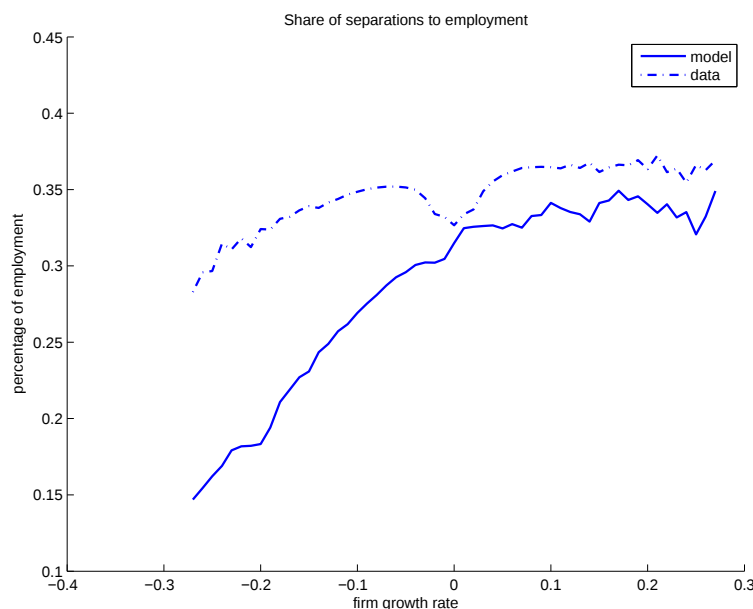


Figure 6: Share of separations to employment. Source: model simulation. The solid line in the figure shows the number of workers who separate to employment as a share of all separations, at firms with different growth rates. The dotted line shows the data.

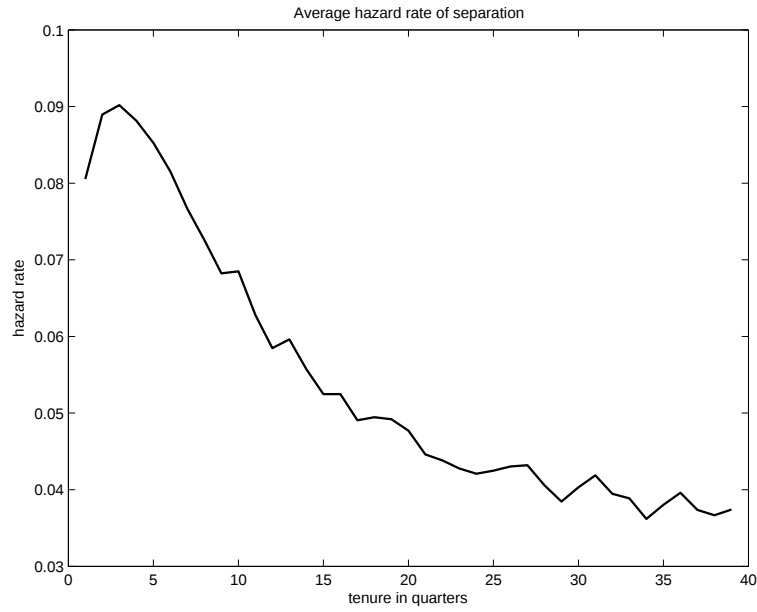


Figure 7: Hazard rate of separation at different tenures. Source: model simulations.

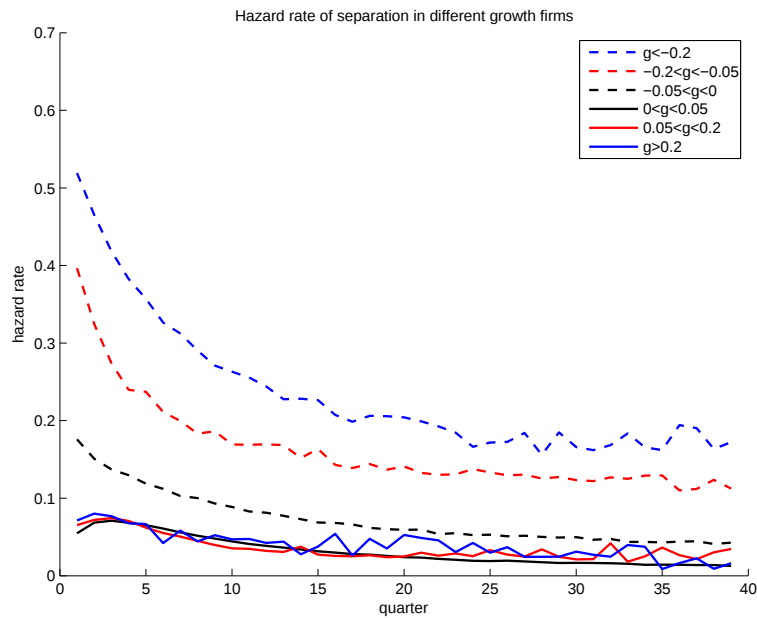


Figure 8: Hazard rate of separation at different tenures, in firms with different growth rate. Source: model simulations.