Separations on the Job Ladder [*]

Kerstin Holzheu [‡]

November 13, 2017

Current Version

Abstract

Using three European matched employer-employee data sets, I show that workers experiencing high positive or negative changes in wages subsequently have a high propensity of job separation. In all three data sets, a change in wages of 10% above or below the median coincides with roughly 20% higher odds of job separation. The effect on job separation is more pronounced among low experience workers. Theoretically, I rationalize the empirical finding as a result of information and labor market frictions in a random search model with two-sided heterogeneity and symmetric learning about worker ability. In the framework, workers with low experience have a high initial volatility of wage changes and move between firms to enjoy productivity benefits. I allow for additional channels of wage growth through contract renegotiation and dynamic match productivity and let firms differ in the volatility of production shocks. In the model, workers can partially reduce their wage exposure to productivity shocks by accumulating wage negotiation capital such that the volatility of wage changes falls endogenously on the job ladder. An uneven distribution of volatile firms along the job ladder further increases wage stability with experience. I thereby show that the job ladder does not only determine worker's level of wages but can also account for part of its variability.

JEL Classification: E24, E25, J24, J31, J63, J64
Keywords: Separations, Wage Dynamics, Learning, Job Ladder

[‡]PhD Candidate University of Chicago, kholzheu@uchicago.edu.

1 Introduction

On-the-job wage growth and job separations are ubiquitous features of a young worker's career. On average, 66% of lifetime wage changes and a roughly equal share of separations occur during the first ten years of a worker's labor market experience.[1] This paper analyzes the relationship between early career wage changes and separations.

Using matched employer-employee data for three European countries, I detail and explain a previously undocumented U-shape pattern between wage changes and separations; above and below median wage growth on the job coincides with an elevated propensity of job separation (cf. figure 1, left panel). I show that this fact is especially pronounced for inexperienced workers (cf. figure 1, right panel). In all three European samples, a 10% change in real wages leads to a rise in the odds of separation of about 20%. Hence, workers experiencing both wage rises and wage declines face an increased likelihood of job separation.
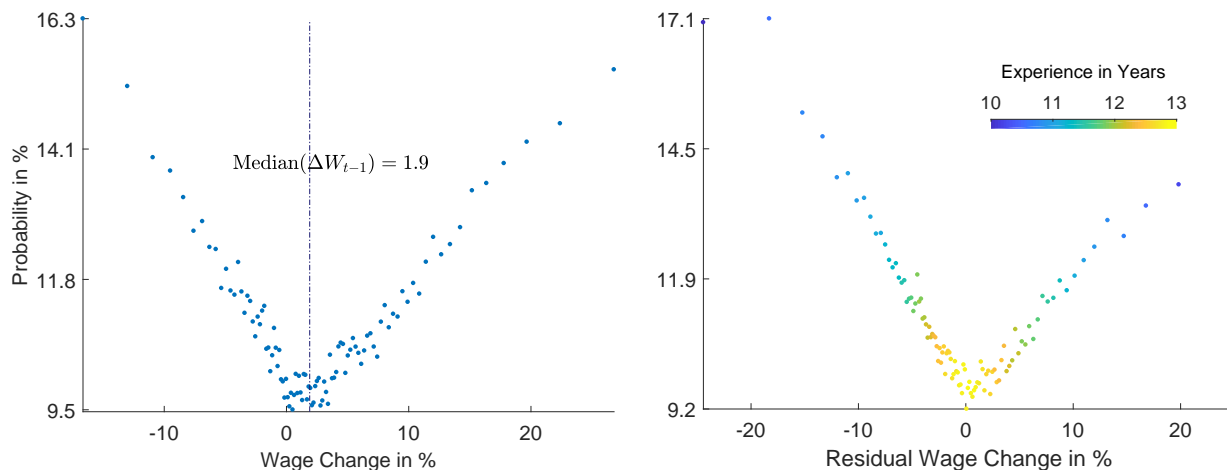

Figure 1: The U-Shape between Wage Changes and Separations (Italy)

The figure shows the average separation rate at time t for workers experiencing wage changes at time $t-1$ within centiles of the distribution of wage changes (left panel) and within centiles of the distribution of changes in residual wages (right panel). The right figure features color coding for mean experience in years.

I explain this empirical pattern by developing a random search model with information frictions and worker resorting on the *job ladder* (as introduced by Pinheiro and Visschers (2015)). In the model, young workers experience an elevated variance of wage changes. At the same time, workers move up the ranks of the job ladder towards better jobs, such that the variance of wage changes and the separation propensity decline simultaneously. Three mechanisms account for the decline of the variance of wage changes in the model. First, the

---

[1]cf. Topel and Ward (1992)

volatility of wage changes falls as workers are increasingly certain about their productivity. Second, workers can partially insure against productivity shocks by accumulating renegotiation capital through on-the-job search. Finally, the variability of wage changes falls with experience due to an uneven distribution of volatile firms along the job ladder.

The investigated relationship between wage changes and separations sheds light on the pervasive instability of early careers. Empirically, the paper shows that both workers with negative and positive wage evolution face a higher propensity of job mobility. Yet job mobility in itself has been shown to lead to significant wage variability. Precisely, wage gains at job changes have been shown to account for as much as one third of wage growth in the first ten years of a worker's career (cf. Topel and Ward (1992)). Hence, the co-occurrence of on-the-job-wage growth and separations depicts a systematic and mutually reinforcing pattern of wage instability for young workers.

This paper relates to the large empirical literature concerned with the description of age-earnings profiles and its relationship to separations over the life cycle. In particular, Topel and Ward (1992) estimate a negative effect of prior wage growth on separations, when controlling for the current wage level, using US Longitudinal Employee-Employer Data (LEED). This finding has been replicated in a number of countries and data sets but stands in contrast to a small set of studies which find wage changes and separations to be independent[2]. In this paper, I show the existence of a U-shape relationship between wage changes at the job and the probability of job separation using matched employer-employee data for Italy, Austria and Germany. To the best of my knowledge, the paper is the first to provide a comparative perspective using three matched employer-employee data sets. All three countries feature more rigid labor market institutions as compared to the US economy, yet they differ largely among each other. In particular, the Austrian and German labor market have been known for relatively low unemployment rates as compared to the Italian economy. Moreover, short-term contracts were largely non-existent in Italy over the time period in consideration, while pervasive in Germany and Austria. Finally, wage negotiations have traditionally been highly centralized in Italy and Austria, whereas more decentralized bargaining has been operative in Germany. I hence conclude that my results are not driven by idiosyncratic features of a

---

[2]For a negative effect, consider Bingley and Westergaard Nielsen (2006) with Danish matched employer-employee data, Liu (2015) using the Survey of Income and Program Participation, Galizzi and Lang (1998) for Italian data. Relatedly, McLaughlin (1991), using the PSID, finds that predicted wages at the job have a negative effect on separations. In data for California's Civil Servants, Kim (1999) finds a negative effect of average wage changes on turnover rates. For the US NLS data set, Kahn and Griesinger (1989) and Bartel and Borjas (1978) find a negative relationship between wages and quits. Yet, for Portugal, Klaauw and Silva (2011) show that wage increases do not forecast job separations. Solnick (1988) studies quit behavior at a (non-specified) firm and finds that salary changes do not significantly affect quitting.

single labor market but rather reflect a more widely observable economic pattern. I further show that the U-shape relationship between wage changes and the separation propensity is driven both by the experience of a worker and the type of the firm she is working for. Moreover, I show that the U-shape pattern is not the result of the intersection of two monotone relationships between wage changes and separations describing quits and layoffs. Lastly, I provide evidence that the effect is not dominantly driven by occupational changes.

The paper also relates to the theoretical literature on separations. Traditionally, the theoretical rationale for an effect of wage changes on separations has been built on dynamic models of match specific productivity. In mismatch theories of separations, such as Jovanovic (1979) where workers learn about constant match quality, or Prat (2006) and Liu (2015) featuring a random walk model of match productivity, wage changes reflect evaluations of the match quality between workers and firms. Yet in these models, decision rules for separations are decreasing functions of reservation wages, such that wage changes have no predictive power for separations once wage levels are taken into account.[3] Models describing learning dynamics and their effect on occupational switching (cf. Groes et al. (2015), Perticara (2004), Pfeifer and Schneck (2012), Papageorgiou (2013), Gielen and Ours (2006), Neal (1999), Gibbons and Waldman (1999)) have the potential to explain increasing separation rates as evaluations about worker's ability increase. For instance, Groes et al. (2015) show with Danish matched employer-employee data that workers at both extremes of their occupation's wage distribution are more likely to switch occupation and rationalize their finding within a model of learning about worker's skills. Yet also in these models, given the martingale property of wage changes as a result of learning, wage changes have no predictive power for occupational switching once the relative wage level of a worker within the occupation is taken into account.

In this paper, I argue that the variance of wage changes (rather than the wage level) is indicative of potential future separations by proxying for an early career stage. In my model, separations along the U-shape are the result of differences in absolute, rather than comparative productivity advantages across firms. As workers ascend on the job ladder, the likelihood of separations decreases given a constant job finding rate of randomly drawn job offers. My theoretical model extends the random search framework of Jarosch (2014) by allowing for learning about a worker's type and autocorrelated innovations to match specific productivity. In particular, as workers source outside job offers, wage renegotiation has the potential to mitigate the impact of productivity shocks on the current wage, thereby reduc-

---

[3] Munasinghe (2000) allows for the relevance of wage growth conditional on wage levels by assuming firm heterogeneity in wage growth rates. However, this explanation cannot rationalize a positive relationship between wage growth and separations over some range of the support of wage changes.

ing the volatility of wage changes. To my knowledge, this is the first paper to feature a mechanism in which the volatility of wages declines through the accumulation of negotiation capital on the job ladder. Differences in the volatility of innovations to match productivity, distributed unevenly across the job ladder, have the potential to further create a coincidence of high wage volatility and an elevated propensity of job separations to more productive matches. By jointly analyzing learning and the job ladder, the paper is related to a small literature examining the dynamics of learning during the process of job matching (cf. Eeckhout and Weng (2009), Borovickova (2013)). By evaluating the quantitative saliency of learning theories, this research similarly relates to Lluis (2005), which estimates the occupational switching model of Gibbons and Waldman (1999) using wage rules. Finally, it relates to Kahn and Lange (2014) who estimate the potency of learning and dynamic match productivity in shaping wage patterns in the data. My paper advances on this literature by allowing for a concurring impact of job ladder effects in an equilibrium model. I calibrate the model with the simulated method of moments using separations together with various wage moments. I do not target the U-shape pattern directly and show that deviations of the parameters lead to considerably different patterns between wage changes and separations. Finally, I use the theoretical model to evaluate the effect of a partial decentralization of wage bargaining on the effect of the variability of wage changes. I show that decentralization can in fact reduce wage inequality within groups of workers, despite increasing overall inequality between workers. This effect is due to the insurance effect of negotiation capital in the model.

In the following, I outline the data source (cf. section 2), and describe the econometric results (cf. section 3). I then lay out the partial equilibrium model to explain the U-shape result in a model with learning of match quality and a job ladder (cf. section 4). In this section, I also describe the model's calibration and results.

2 Data

2.1 Overview

I use three linked employer-employee data sets to estimate the main effect and to address concerns about external validity. Specifically, I use the Italian Veneto Worker Histories VWH, the German matched employer-employee data set LIAB and the Austrian AMDB. All three data sets have been constructed using administrative records from social security insurers. They differ first and foremost in their sampling design. The German matched employer-employee data set LIAB is populated around representative draws from the IAB establishment panel, whereas the Italian and Austrian data sets are constructed around the

universe of firms, either for two provinces in the North-East of Italy or for the territory of Austria. The Italian VWH data set covers the longest time span (1975 to 2001), as compared to the German LIAB (1993-2010) and the Austrian AMDB (2000-2016). The German LIAB features a larger set of information on education, firm characteristics and occupations, yet contains the full set of coworkers only for the years 1999-2009. The Austrian data set AMDB is comprehensive in its coverage of coworkers, but contains a limited number of observables on workers.

I now present the scope of each data set in turn and then describe the sample selection applied to all data sets.

2.2 Italian Veneto Worker Histories

The Veneto Worker Histories (VWH) cover all wage workers in the private sector in the provinces Treviso and Vicenza in the North-East Italian region Veneto for the period 1975-2001. It further contains the work history of all firm associated workers during the sampling period. The data includes information on gender, age and residency of the workers. Information on the firm covers the age of the firm, the location of the seat of the firm and the sector of its economic activity. The data set contains information on each employment spell during a year, including total real earnings and weeks worked at the job, the start date and cessation date as well as the qualification at the job (worker or manager, for instance) and the nature of the job (temporary or with undetermined duration, full-time or part-time) as well as the contract type. There is no information on education, yet the literature has argued that categorial information on the skill level provides a partial control for education levels (cf. Galizzi and Lang (1998)). I construct weekly wages using the information on total wages (non-top coded) earned at the job and weeks at the job. While using similar vintages of the data, Galizzi and Lang (1998) applies a monthly wage concept and Serafinelli (2013) a daily wage concept. I follow Tattara and Volpe (1999) using a weekly wage concept. I experimented with all three time measures and did not find significant differences (cf. Appendix 6.3.4 for more details). The recorded income includes extraordinary wage payments such as overtime pay but excludes other types of payments that affect household income such as social security payments. For a detailed description of the data cf. Tattara and Valentini (2010), Leonardi and Pica (2013), Ibsen et al. (2008), Grinza (2014), Bartolucci et al. (2015), Serafinelli (2013).

2.3 German LIAB

The linked employer-employee dataset LIAB combines administrative records from the Federal Employment Agency (BA) with plant-level data from the Establishment Panel of the

Institute of Employment Research (IAB) for the years 1993-2010. For a stratified and nationally representative draw of firms in operation during the years 2000-2008, the sample covers the full employment history of all firm associated workers in the years 1999-2009 and collects the work histories for all workers as far back as 1993. The data set includes information on employees subject to social security contributions and excludes civil servants, family workers and students in higher education. The main variables from the data set used in this study include information on the start and end of employment spells, the type of work (temporary, full-time), the age of the worker, and the sector of economic activity of the firm. In addition to information on employment spells, the data also includes information on employment benefits received by the worker such that layoffs and quits can be distinguished.[4] The data set further differs from the Italian records for Veneto in that it includes information on education and a detailed characterization of occupations at the three digit level. The wage information available in the LIAB is daily gross wages up to the earnings ceiling for social security contributions. I deflate wages using the CPI deflator with base year 2010. For detailed description of the data set cf. Klosterhuber et al. (2014) and Fischer et al. (2008) for a detailed description as well as Card et al. (2013), Hirsch and Zwick (2013), Addison et al. (2008), John T. Addison (2010), Addison et al. (2015), Guetzgen (2007).

2.4 Austrian AMDB

The Austrian AMDB dataset is co-constructed by the federal ministry of economics and labor (BMWA) and the labor service institution (AMS) based on social security records. It contains the universe of employment spells and social security benefits for Austrian workers during the time period 2000-2016 and covers start and end date, total earnings and days worked at each job for each month of the year. Moreover, the AMDB includes information on the economic sector at the 4-digit level and the work place location as well as age in 5 age groups, yet it does not contain information about the educational attainment or the occupation of a worker. For consistency with German and Italian data, I aggregate the wage information for each spell to the annual level. The recorded income is subject to a single, nationally uniform reporting limit. I adjust observed nominal wages using the CPI deflator with base year 2010. For a description of the data set, cf. here. For additional information, consider Zweimüller et al. (2009) and Borovickova (2013) using a similar data set.

---

[4]German labor law requires 12 months of consecutive social security payments to be eligible for unemployment benefits after declaring oneself unemployed. By our sample design, everybody in the sample fulfills eligibility, yet workers might decide not to declare themselves unemployed for idiosyncratic reasons.

2.5   Sample Selection

The sample is restricted to full-time work spells of male workers of at most 30 years of age at entry into the data set. This restriction aims at reducing measurement error of observed labor market experience. In a robustness exercise, I do not find qualitative differences when delaying the start date of the data set (cf. Appendix 6.3). The lower age limit is set to 16 years. Apprentices and workers in training are excluded from the sample due to potential differences in the work contracts. In robustness exercises, I study the baseline specification including apprentices. I did not find qualitative differences, cf. details in Appendix 6.3. I further restrict attention to full-time spells with undetermined duration. I exclude spells with periods of parallel work at different firms and censored observations for Germany and Austria. There is both an upper ceiling and a lower floor on wages subject to social security contributions in Germany. For the upper ceiling two potentially binding thresholds (one each for East and West Germany) exist, depending on the social security organization that the worker belongs to. I conduct robustness exercises regarding censoring for both Austria and Germany in Appendix 6.3.5. For cases of multiple observations at one firm during a single year, I compute a weighted single wage observation.[5]

Moreover, I also exclude some observations due to their unusual nature of separation. As such, I exclude spells that end with the disappearance of the firm from the data set as well as mass layoffs as far as measurable. Specifically, I follow Schmieder et al. (2010) in the definition of mass layoffs at instances in which a firm separates from more than 30% of its work force of the previous year. This definition implies that the size of the firm in two consecutive periods as well as the total number of separating agents have to be known. If this criterion cannot be computed due to missing data, I do not exclude the observation. I further exclude spells ending in the death of the worker (for Germany) as well as spells with separations in every single observed year to exclude potential seasonal work arrangements.

Finally, I only consider work spells featuring full-year work in each period during the duration of the contract, excluding the last and first observation if separations occur during the year. In this way, I reduce measurement error in wage growth and exclude non-standard working situations. Similarly, I require that wage changes are computed for full year observations in order to allow for a valid wage change measurement. The rationale is that wage observations relative to years with less than 12 months of work have a higher likelihood of carrying

---

[5]I also experimented with excluding these observations but did not find qualitative differences, mainly as my empirical specification requires at least two full year observations at the firm. The primary focus of interest of this paper is separations from one firm to another and not separations with rehires at the same firm due to the variety of potential interpretations of rehires.

measurement error which would increase observed wage change variance during years of separation. This timing convention also follows Liu (2015). Figure 2 represents the timing in the data. For a worker in firm A, I require at least two full year observations to compute ΔW_{t-1}. The object of interest is the probability of separating conditional on ΔW_{t-1}. Wage changes are computed as differences of log wages. In Appendix 6.3 I conduct robustness exercises with respect to the arc percentage of wage changes but do not find qualitative differences. Finally, I limit my attention to the 98% of the support of wage changes. Due to potential measurement error in the reporting of payed leave in the Italian data, as reported in Galizzi and Lang (1998), I further experimented with different trimming of the extremes of the wage change distribution but did not find qualitative differences (cf. Appendix 6.3.4).
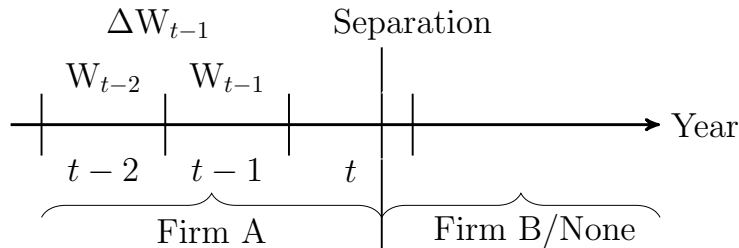

Figure 2: Timing

2.6 Sample Description

Table 8 (cf. Appendix) summarizes the three samples. Overall, the median age is 35 and 34 years, partly by construction through capping the entry age at 30 years. The median tenure varies with the maximum length of the data set, with a low median tenure of 4 years for the German LIAB and up to 6 years in the Italian data set VWH. Similarly, median observed labor market experience ranges from 13 years in Italy to 9 in Austria's AMDB. The mean wage growth is highest in the AMDB sample with 2.98 %, and lowest in the LIAB sample with 1.85%. The average separation rate is highest in the LIAB sample with 16.2% and lowest in the AMDB with 9.2%. The Italian sample features an average separation rate of 11%.

These numbers compare well to the literature. Using the European Union's Labour Force Survey for 2014, Maria Symeonaki and Karamessini (2014) find an average separation rate of 11.85 for the Italian and 12.5 for the Austrian work force aged 15-24 years. The average wage change rate for Italy of 2.65% can be compared to an average of 2% wage growth for the year 1982/1981 in Galizzi and Lang (1998). Similarly to our estimates, Lluis (2005) reports

9

a separation rate of 17 % and an average on-the-job wage growth rate of 1.92 % for male workers with 0-10 years of tenure for the German data set GSOEP (compared to a mean of 1.85 in our sample) for the period 1985-1996. Similarly, Anger (2011) finds average wage growth rates of around 2-2.4% for the period 1984-2005 in Germany with workers aged 20-60.[6]

Due to its geographical focus on a highly industrialized region, the Italian data set has the highest share of observations from the manufacturing sector with 54%, followed by Austria and Germany with 39% and 33% respectively. For comparison, note that Grinza (2014), using a similar vintage of the Italian data, reports 65% of her sample in manufacturing.

3 Empirical Results

3.1 Overview

In the following, I document the main empirical fact, which is a U-shape pattern relating wage changes on the job and the propensity of job separation. I then show that experience affects the strength of the U-shape pattern.

3.2 Empirical Framework

In order to estimate the change in the probability of job separation of worker i at firm j at time t due to wage changes at time $t-1$, $\Delta W_{i,j,t-1}$, I use four approaches. First, I provide a non-parametric estimate of the sample probability of separation at period t after observing a wage change in period $t-1$ for a set of grid points on the support of wage changes. In my main specification, I obtain the grid points by binning the support of wage changes into deciles.[7] In this approach I do not control for covariates. Second, I estimate a logit model on the set of grid points. By presenting both a parametric and a nonparametric estimate, I reduce the scope of potential functional misspecification. Moreover, the double approach allows me to express the difference in the separation probability for a worker experiencing above or below median wage changes both in relative terms (as a multiple of the odds of separating at the median wage change bin) and in absolute terms (as percentage points). Third, I estimate a linear probability model of the probability of job separation on a quadratic function of

---

[6] Fuchs-Schündeln et al. (2010) estimate lower wage growth rates for the post-reunification period of less than one percent but point to differences in microdata and aggregate estimates due to wage estimation in the GSOEP. Given extensive wage moderation during the post-crisis period, I expect my estimate to be lower than Anger's finding.

[7] I will use quintiles instead of deciles in some analysis to increase within-bin sample size. The figure in the introduction, on the other hand, was computed on centiles of the wage distribution. I do not find significant differences with respect to the number of bins.

wage changes while controlling for an array of covariates. The use of the linear probability model aims at facilitating interpretations in light of the well documented difficulties with the interpretation of different logit specifications across samples and specifications due to changes in the variance of the latent variable, cf. for instance Allison (1999). Finally, I also obtain the change in residual wages by controlling for a set of covariates and estimate a logit model within deciles of residual wage changes.

Specifically, the non-parametrical estimate of the separation rate within bins $k = 1, ..., 10$ of real wage changes $\Delta W_{i,j,t-1}$ is obtained as

$$\Pr(\text{Separation}_k = 1) \quad = \quad \frac{1}{N_k} \sum_{i=1}^{N_k} \text{Separation}_{i,j,t}$$

I obtain the logit specification as

$$\text{logit}\left\{\Pr(\text{Separation}_{i,j,t} = 1)\right\} \quad = \quad \sum_{k=1}^{10} I_{\Delta W_{i,j,t-1} \in k} \beta_k + \epsilon_{i,j,t}$$

where $I_{\Delta W_{i,j,t-1} \in k} = 1$ if $\Delta W_{i,j,t-1} \in$ bin k. The linear probability model instead is

$$\text{Separation}_{i,j,t} \quad = \quad \alpha + \beta_0 \Delta W_{i,j,t-1} + \beta_1 \Delta W_{i,j,t-1}^2 + x_{i,j,t-1} \beta_x + \eta_{i,j,t}$$

where $x_{i,j,t-1}$ is a set of control variables.

3.3 A U-Shape in Wage Growth Rates and Separations

The main fact is depicted in figure 3 for the three samples. On the left axis, the figure shows the separation rate at time t as a function of the change in wages at time $t - 1$ in percent. The right axis represents the odds ratio of separating conditional on being in wage change bin k relative to the median wage change bin as estimated in the logit model. Each dot represents about 60K observations for Germany and around 200K for Italy and Austria. For the non-parametric estimate, I compute standard errors using the linear within-bin predictor of separation rates.

Figure 3 shows that both falls and rises in wages increase the propensity of match separation. For instance, a wage rise or fall of about 10 percentage points above or below the median wage change increases the separation probability by about 2 percentage points in the case of Italy. Similarly, this case represents a change in the odds of separating of roughly

11

20%.[8] The effect is statistically significant and economically meaningful. To compare this effect to the change in separations after changes in the aggregate unemployment rate, consider Haltiwanger et al. (2017) for the US. The authors estimate that a reduction in the aggregate unemployment rate of 1% increases the separation rate by 1 to 2 percentage points. In figure 4, I report the logit specification for residual wage growth (cf. also Appendix table 10 for a direct comparison with the baseline specification). In this specification, I obtain residual wage growth as the change in residual wages after controlling for sector, qualification/education (if available) and year fixed effects as well as quadratic polynomials for tenure and experience. Note that in the case of Austria, I do not observe either education nor qualification at the job. Even after controlling for experience, sector and qualification effects, there is a significant U-shape. This result implies that the U-shape pattern is not driven by education or sector differences. When compared to the literature and most notably Topel and Ward (1992), the figure surprises by the upward trend on the right hand side of the support of wages.

Yet, the non-monotonic relationship between wage changes and separations could be the result of the co-occurrence of two separate monotonic relationships. On the one hand, falling match productivity could lead to wage declines and a higher layoff propensity. On the other hand, increases in worker's productivity could motivate search for new job opportunities, thereby increasing the propensity of quitting. Taking this case into consideration, I construct the main figure for quitters alone. For the case of the Italian data set, I do not observe social security benefits and for that reason, I count as quitters all those workers that enter a new employment spell no more than 2 months after the end of the last spell. The German and Austrian samples allow to distinguish between quits and layoffs through the observation of unemployment benefits. In these datasets, I define layoffs as instances in which an employee receives unemployment benefits in between consecutive work spells and quits as instances without such payments. Quitters are then defined as the residual group of workers. The timing in the sample allows to make this definition of layoffs precise. In Germany, the minimum duration of social-security relevant employment required before eligibility for unemployment benefits is 12 months, the same as in Austria for employees requesting benefits for the first time.[9]. As the sample selects workers that have worked

---

[8]For ease of interpretation, let me recall the relation between the odds ratio and the ratio of separation probabilities. The odds ratio, defined as $\frac{p_k}{1-p_k}/\frac{p_b}{1-p_b} = \frac{p_k}{p_b}\frac{1-p_b}{1-p_k}$ where p_b is the probability of separating at the median category and p_k the probability of separating within bin k, is less than 5% higher than the ratio of the within-bin probability to the median probability $\frac{p_k}{p_b}$ over the relevant range of $p_k < 15\%$ for Italy and less than 10% apart for Germany in the relevant range up to $p_k < 24\%$.

[9]Precisely, a worker needs to have completed 12 months of social security relevant employment during the last two years in Germany. In Austria, a worker must have payed social security contributions for at

full-time for at least 2 consecutive years, this requirement is fulfilled for all workers in the sample. Figure 5 visualizes the average probability of job-to-job transition or transition into unemployment for quintiles of the wage distribution. First, the figure shows the well-known result that quits compose the majority of separations in the data. Second, the figures show that the U-shape is not the result of the overlay of two monotonic relationships between wage growth and separations, one for quits and one for layoff. Rather than observing a one-sided relationship for both layoffs and quits, these figures show a non-monotonic relationship especially for quitters. In Appendix table 11, I estimate the linear probability model

$$\text{Separation}_{i,j,t} = \alpha + \beta_0 \Delta W_{i,j,t-1} + \beta_1 \left(\Delta W_{i,j,t-1} \right)^2 + \epsilon_{i,j,t}$$

for the subsamples alone. The estimates confirm that there is a significant U-shape effect for quits and layoffs.

At first sight, the observed relationship between wage changes and separations could also mask a relationship that has previously been documented in the literature. The pattern could reflect a U-shape relationship between the relative position of a worker in his respective occupation and his likelihood of occupational switching (cf. Groes et al. (2015) for Danish and Perticara (2004) for US data). To speak to this fact, I test weather the U-shape pattern pertains after controlling for a worker's position in his occupation. The available data on occupations varies across samples. The German LIAB features a description of occupations at the three digit level (in addition to sector information).

---

least 52 weeks during the last 2 years. If an employee has been previously unemployed in Austria, she has to have worked for at least 28(26) weeks in the last calendar year (for employees younger than 26).
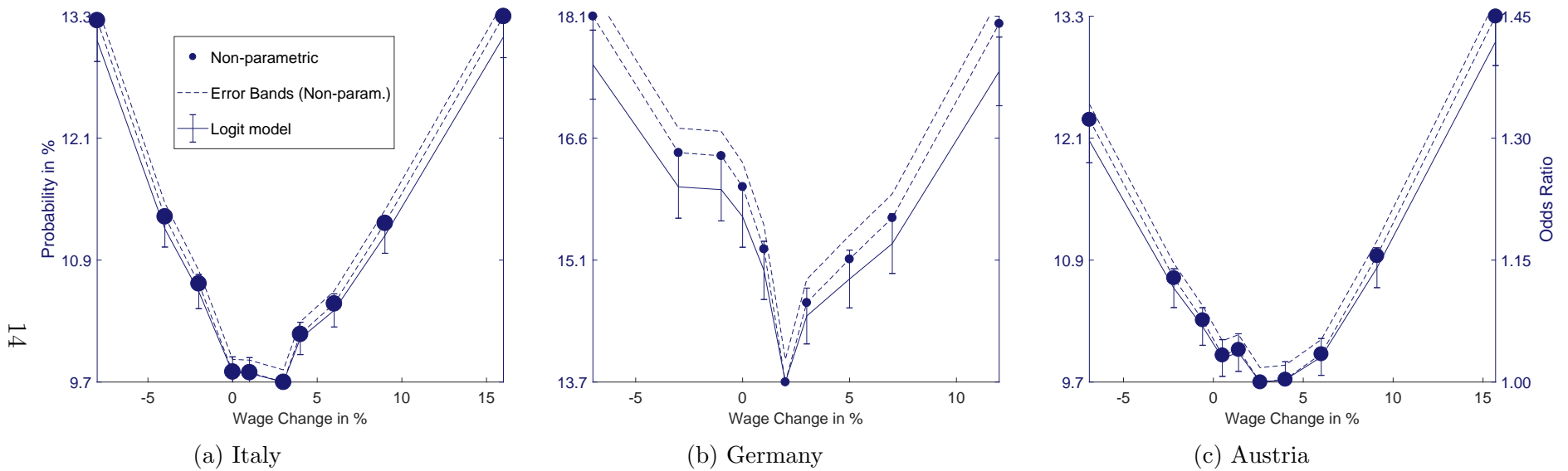
Figure 3: The U-shape relation between wage growth and separation propensity

The figure shows the separation rate of workers at time t as a function of the change in wages at time $t-1$ as a non-parametric within-bin estimate (left axis) and in terms of the odds ratio of separating with respect to the median wage change bin (right axis). The right hand axis is aligned across figures. Each dot represents about 60K observations for Germany and around 200K for Italy and Austria. For the non-parametric estimate, standard errors are computed using the linear within-bin predictor of separation rates.

(a) Italy   (b) Germany   (c) Austria
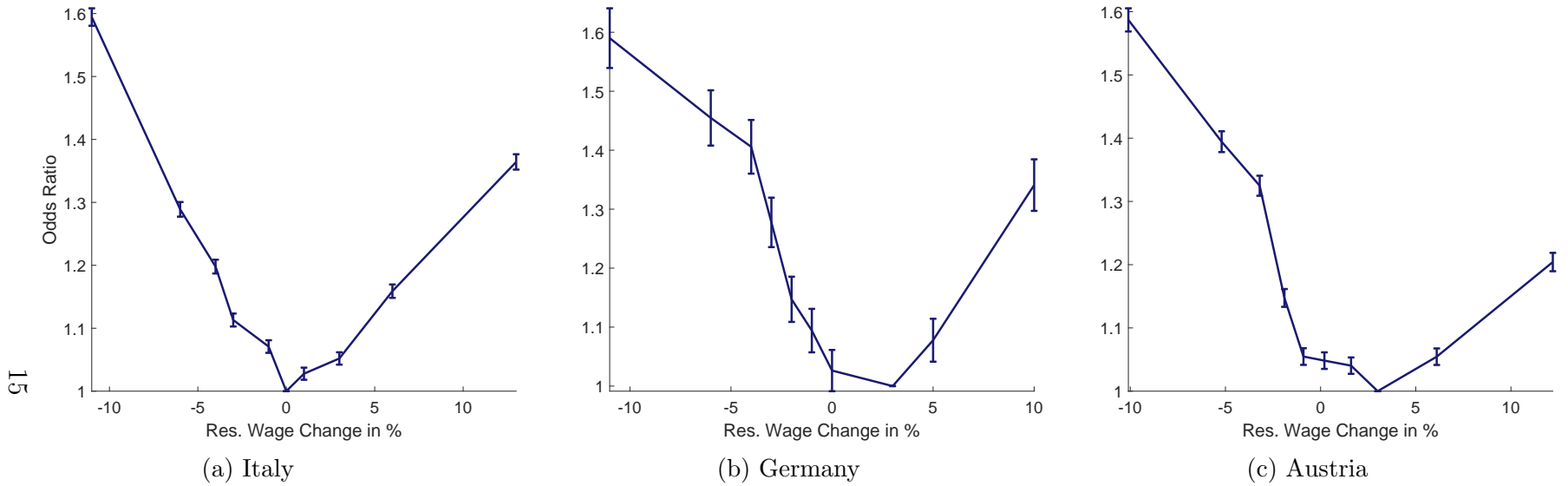
Figure 4: The U-shape relation between residual wage growth and separation propensity

The figure shows the separation rate of workers at time t as a function of the change in residual wages at time $t-1$ in terms of the odds ratio of separating with respect to the median residual wage change bin. Residual wage growth is obtained as the change in residual wages after controlling for sector, qualification/education (if available) and year fixed effects as well as quadratic polynomials for tenure and experience.
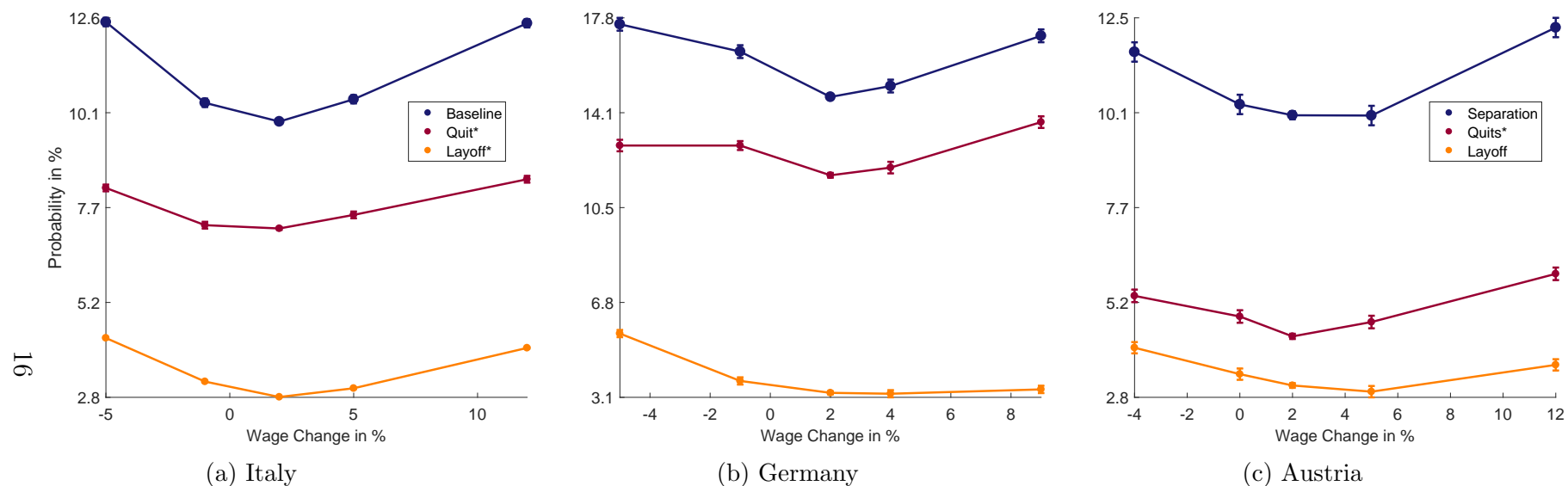
Figure 5: The U-shape and differences after separation

The figure shows the separation rate of workers at time t as a function of the change in wages at time $t-1$ as a non-parametric within-bin estimate, separately for layoffs, quits and separations overall. For the Italian data set, quitters are defined as all workers with no more than 2 months of non-employment after the end of the last employment spell, for the German and Austrian samples quitters are defined as workers that do not receive unemployment benefits after an employment spell. Layed-off workers are defined as the remaining category of workers.

The Italian VWH allows to construct occupations as the interaction of sector identifiers and a five level qualification indicator. Short of occupation information, I use information on the sector in the Austrian AMDB data set. I then construct the relative position of a worker in his respective occupation/sector wage distribution $W_{t-1} - \mu(W_{t-1})^o$ within each year. I find that the effect of wage growth rates on separations is robust to controlling for the relative position of the worker in his occupation (cf. table 1). As the cited authors, I do find a (weak) U-shape relationship for all three datasets (cf. figure 15 in the Appendix) between the relative wage of a worker and his probability of occupational switching. In Appendix 6.4 I further consider the direction of moves of workers on the U-shape. Especially for Italy, I find that workers on average move to firms with higher wages and lower volatility. I hence conclude that occupational switching, that would predict movements to firms with on average lower wages for those workers with declining wages, is not the dominant driver of the observed pattern.

	Italy		Germany		Austria	
	Δ Occ.	Sep.	Δ Occ.	Sep.	Δ Occ.	Sep.
ΔW_{t-1}	-0.0081	-0.074***	-0.023	-0.043***	-0.041***	-0.039***
	(0.0043)	(0.0058)	(0.011)	(0.011)	(0.0027)	(0.0037)
ΔW_{t-1}^2	0.88***	1.50***	0.98***	1.44***	0.39***	1.04***
	(0.028)	(0.038)	(0.090)	(0.093)	(0.015)	(0.020)
$W_{t-1} - \mu(W_{t-1})^o$	-0.044***	-0.11***	0.0017	-0.052***	-0.020***	-0.042***
	(0.0011)	(0.0015)	(0.0021)	(0.0022)	(0.00045)	(0.00060)
$(W_{t-1} - \mu(W_{t-1})^o)^2$	0.078***	0.056***	0.030***	0.033***	0.015***	0.049***
	(0.0019)	(0.00058)	(0.0031)	(0.0034)	(0.0026)	(0.0026)
Constant	0.046***	0.10***	0.039***	0.053***	0.061***	0.11***
	(0.00028)	(0.00039)	(0.00057)	(0.00062)	(0.00018)	(0.00024)
Observations	.8M	.8M	.2M	.2M	2M	2M

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ Occ. denotes occupational switching

Table 1: Wage Growth and the Relative Position of a Worker

3.4 The Experience Effect on the U-Shape Relationship

Understanding the variability of the U-shape pattern with experience guides the theoretical framework in the next section. Low experience workers that learn about their type feature increased variance of wage changes at the beginning of their career, while simultaneously being more likely to separate to better firms. In the following, I document the effect of experience on the U-shape effect, supporting this interpretation of the empirical pattern.

To test for an experience effect, I use a linear probability model and estimate the following specification in which I interact the quadratic form in wage changes with lagged experience.

$$\text{Separation}_{i,j,t} = \alpha + \beta_0 \Delta\mathrm{W}_{i,j,t-1} + \beta_1 \left(\Delta\mathrm{W}_{i,j,t-1}\right)^2 + \beta_x \mathrm{Exp}_{i,j,t-1}$$
$$\beta_{x0}\left[\mathrm{Exp}_{i,j,t-1} \times \left(\Delta\mathrm{W}_{i,j,t-1}\right)\right] + \beta_{x1}\left[\mathrm{Exp}_{i,j,t-1} \times \left(\Delta\mathrm{W}_{i,j,t-1}\right)^2\right] + \epsilon_{i,j,t}$$

The results are shown in table 2. In all samples, workers with higher experience feature less pronounced U-shapes. As the interaction effects between experience and the quadratic and linear terms of wage growth are negative, experience reduces the size of the U-shape pattern and reinforces a negative relationship between wage changes and separations. In addition to testing for an experience effect, table 2 also controls for the lagged growth rate of the firm in terms of full-time employees. This allows to counter possible mechanism that built on evolving mismatch of workers and firms as in Borovickova (2013). The specification further controls for lagged firm size and lagged tenure.[10] To address concerns about measurement

	Italy		Germany		Austria	
	(a)	(b)	(a)	(b)	(a)	(b)
ΔW_{t-1}	-0.085***	-0.14***	-0.07***	-0.11***	-0.034***	-0.06***
	(0.0036)	(0.0058)	(0.011)	(0.011)	(0.004)	(0.011)
$(\Delta W_{t-1})^2$	1.47***	1.67***	1.69***	2.72***	1.27***	1.59***
	(0.023)	(0.058)	(0.071)	(0.29)	(0.027)	(0.060)
$(\Delta W_{t-1})^2 \times \text{Exp.}_{t-1}$		-0.046***		-0.13***		-0.10***
		(0.0055)		(0.025)		(0.0075)
$(\Delta W_{t-1}) \times \text{Exp.}_{t-1}$		-0.002*		0.007*		-0.005***
		(0.0009)		(0.0032)		(0.0012)
Exp._{t-1}		-0.0024***		-0.0068***		0.0027***
		(0.000067)		(0.00019)		(0.000080)
Constant	0.66***	0.47***	0.51***	0.17***	0.49***	0.41***
	(0.0038)	(0.0070)	(0.0060)	(0.0079)	(0.0034)	(0.0034)
Observations	2.3M	.9M	.6M	.2M	1.8M	1.8M

(b) controls for $\Delta N_{j,t-1}$, $N_{j,t-1}$, $\text{ten}_{i,t-1}$, $W_{i,j,t-1}$, (a) for $W_{i,j,t-1}$.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Experience Effect

errors regarding experience, I conduct a robustness exercise in table 14 where I use age rather than observed labor market experience as a proxy for past years in the labor market. Except for Germany, where the interaction effect with wage growth is not significant, results

___

[10]The extend of the U-shape in this quadratic specification for the linear probability model can be gauged by comparing the two coeffients of the quadratic form. Recall that the vertex is obtained as the negative of the ratio of the linear and the quadratic term, divided by two. Hence a low quadratic and linear term signal a weak U-shape pattern.

are quantitatively similar.[11] The result could also be driven by workers' heterogeneity in the idiosyncratic volatility of productivity such that high volatility workers would be more likely to feature a U-shape. To test for this channel, I split the sample into below and above mean volatility workers where I estimate the volatility of wage changes over a period of at least 7 years. The results in table 15 in the Appendix show that the U-shape is not stronger for high volatile workers.

The experience effect on the U-shape could mirror a true life cycle effect or simply reflect a composition effect of young workers aggregating at low quality, high volatile firms with high separation rates. To address this channel, I control for firm types in table 13. I construct five firm types based on the average separation rate $\mu(\text{Sep}_{i,j,t})$ of workers out-of-sample composed of workers with more than 30 years of age at the start of the dataset. I then obtain quintiles of the distribution of these separation rates. To avoid erroneous inference due to the estimation of firm quality, I bootstrap standard errors within firm type quintiles at the spell level in column (c) of the table. Column (b) reports OLS results. I find that the experience effect is reduced but remains significant in all three country data sets. Finally, to distinguish experience from tenure effects, I further estimate the linear probability model by interacting wage growth with bins that separate workers by experience and tenure (splitting at below and above mean experience/tenure levels to create four bins). Specifically, I estimate

$$
\begin{aligned}
\text{Separation}_{i,j,t} \;=\; & \alpha + \beta_{x0}\left[\text{Ten}_{i,j,t-1}^{L,H}\times\text{Exp.}_{i,j,t-1}^{L,H}\times(\Delta W_{i,j,t-1})\right] \\
& +\; \beta_{x1}\left[\text{Ten}_{i,j,t-1}^{L,H}\times\text{Exp.}_{i,j,t-1}^{L,H}\times(\Delta W_{i,j,t-1})^2\right] + \epsilon_{i,j,t}
\end{aligned}
$$

where $\text{Exp.}_{i,j,t-1}^{L,H}$ and $\text{Ten.}_{i,j,t-1}^{L,H}$ denote the constructed experience and tenure bins for low and high values, respecively. Table 14 shows that the effect is strongest for low experience, low tenure workers in all countries. Moreover, the experience effect is stronger than the tenure effect. This results supports the experience effect and thereby shows that life cycle factors, rather than spell-specific effects, are the stronger determinants of the U-shape pattern.

The main empirical results are as follows. First, the probability of job separation is U-shaped in the lagged wage growth at the job. That is, workers that experience not only above, but also below median wage changes have a higher likelihood of subsequent job separation. Second, more experienced workers have flatter U-shape patterns, especially so at

---

[11]Years of schooling are a very imprecise measure of educational attainment in Germany, such that the results could be affected by a very noisy measurement for effective labor market experience. Moreover, the German sample is smaller by a factor of almost ten when compared to the Austrian sample. Both factors likely affect the result.

the right tail of the support of wage changes. We further find that the experience effect is weakened once we control for firm types.

These facts suggest that part of the U-shape phenomenon is due to firm sorting, which commends a model in which workers ascend on the job ladder while experiencing a high volatility of productivity signals. This effect will be central in the following theoretical framework.

4   Theory

4.1   Overview

In this paper, I consider a random search model with on-the-job search and heterogeneity across firms and workers to explain the empirical U-shape effect. Symmetric learning about the type of the worker is the main mechanism driving young workers' variance of wage changes in the model. While workers learn about their type, they also ascend on the job ladder by moving to more productive firms.

This model assumes that wages are determined flexibly in the frame of a renegotiable wage contract such that wage changes can reflect changes in productivity. This assumption is particularly suitable for inexperienced workers that are the focus of this paper. Empirically, it has been documented that inexperienced workers are more likely employed in flexible arrangements (cf. for instance Tealdi (2011) for Italy) than more experienced workers. Theoretically, the literature has shown that in the presence of uncertainty about the quality of workers, the prevalence of flexible contracts can be optimal (cf. for instance Macho-Stadler et al. (2014)).

This framework focuses on learning about the type of the worker to model the increased variance of wage changes at low levels of experience. Other mechanisms could also rationalize a declining experience profile of the variance of wage changes, such as decreasing returns in learning about generalized skills as in Jovanovic and Nyarko (1995). Both frameworks share an early career instability of wages and expected skills. In Appendix 6.10 I argue that learning of skills is not a dominant channel for Italy, but potentially so for Austria.

In the following, I lay out a baseline model able to rationalize the U-shape pattern. I will show in a simple calibration exercise that the model allows for a U-shape pattern. I will then introduce three extensions to capture additional details of the empirical data. Next, I calibrate the model and discuss two implications of the framework. I conclude the section with an application of the model in which I study a partial decentralization of wage

bargaining.

4.2   Model Set-up

4.2.1   Environment and Learning

Time is discrete. The economy is populated by a mass of heterogeneous firms and workers. Both firms and workers are risk neutral and discount the future at rate β. Workers differ in their unobserved and constant productivity a_i and are infinitely lived. Let productivities a_i follow a normal distribution in the population of workers.

Firms vary in their productivity μ_j. Each period, output of worker i at firm j at time t is subject to a productivity shock $e^{n_{i,j,t}}$. Innovations $n_{i,j,t}$ are independent and identically distributed and follow a normal distribution G^J with mean zero and standard deviation σ_j^2. The logarithm of the output process $y_{i,j,t}$ is described as

$$y_{i,j,t} \; = \mu_j + a_i + n_{i,j,t}$$

I follow an additive specification of the production function in light of the finding of Lamadon et al. (2015) who do not find strong evidence against additive worker/firm production specifications. In light of the empirical evidence that suggests that occupational switching is not the main driver of the observed pattern, I neither model differences in production complementarities across firms.

While firm productivity is common knowledge across all members of the economy, workers' productivity is not observed. Yet, by observing output, workers can learn about productivity.[12] At the start of their employment history, workers draw an initial belief from a normal distribution with mean $E[a_i]$ and variance σ_{a0}^2. In the subsequent periods, given normality of initial beliefs and of the output signal, workers update their mean belief $A_{i,t}$ as well as its variance $\sigma_{a,i,t}^2$ (cf. Appendix section 6.6 for details) as

$$\sigma_{a,i,t}^2 = \frac{\sigma_{a,i,t-1}^2}{1 + s_{i,t-1}} \qquad\qquad A_{i,t} = A_{i,t-1} + \frac{s_{i,t-1}}{(1 + s_{i,t-1})}\xi_{i,j,t}$$

---

[12]Hence, workers do not learn about their type when unemployed. A generalization of the framework that would allow for learning when unemployed would be straightforward. Learning when unemployed would merely affect the surplus value (by changing the outside option and the continuation value) but leave the relative attractiveness of, and thereby mobility patterns between, firms unaltered.

where the signal to noise ratio $s_{i,t-1} = \sigma^2_{a,i,t-1}/\sigma^2_j$ and $\xi_{i,j,t} = y_{i,j,t} - A_{i,t-1} - \mu_j$. In the following, I will drop the subscript i whenever the context allows and denote the state vector of the individual, including the current mean belief and its variance, as $I_t = \{A_{t-1}, \sigma_{a,t-1}\}$.

While on the job, workers search randomly for job matches by drawing from the fixed firm distribution $F(J)$ at rate λ^1. Finally, job matches can be terminated exogeneously at rate δ. When unemployed, workers receive unemployment benefit z and search at rate λ_0 for new job offers.[13]

The timing in the model is as follows. Consider a worker at some firm. At the beginning of period t, worker and firm hold beliefs $A_{t-1}, \sigma_{a,t-1}$. Next, wages are paid and the worker can be laid off at the exogeneous rate δ. In the following, output is revealed and both workers update their beliefs. At this point, the new information about the worker can trigger an endogenous separation if the match's surplus value drops below zero. Finally, workers receive outside offers and can either stay at the current firm or leave. The timing is represented in figure 6.
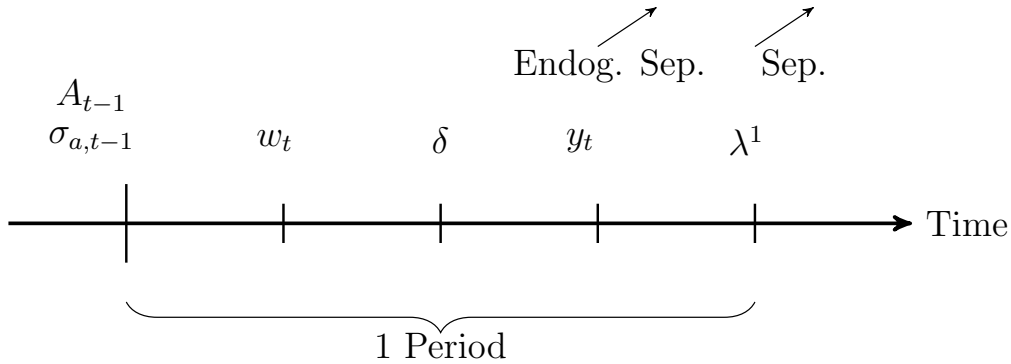
where w_t Wage $\quad \delta$ Prob. Ex. Layoff $\quad y_t$ Output $\quad \lambda^1$ Prob. Job Offer

Figure 6: Timing in the model

[13]This model does not allow for endogeneous search effort as in Christensen et al. (2005), Hornstein et al. (2011) or Topa et al. (2016). Allowing for endogeneous search effort would however strengthen my results by allowing for a lower separation rate of experienced workers at better firm. As more experienced workers at higher ranks of the job ladder optimally reduce search efforts (cf. for instance Topa et al. (2016)), the separation propensity for experienced workers would fall, consistent with the experience effect presented in the empirical section.

4.2.2 Contract, Surplus Function and Wages

In the following, I denote the firm's state vector $J = \{\mu_j\}$. In this baseline model, I will assume that the worker obtains the full surplus of the match. The surplus $S(J, I)$ of the match is then composed of the flow value of expected production net of the unemployment benefit and of the option value of the match. The latter is composed of the option value of search plus the option value of a continued match. As workers can only learn while working, the surplus equation further features an option value of learning $\int U(I') - U(I) dG^J(I')$. Moreover, upon meeting a new firm J' at rate λ_1, the worker potentially moves to the new firm and receives the surplus at the new match. Given the contracting assumptions, she will move whenever the surplus at firm J' exceeds the surplus at her current firm J. The surplus equation is then

$$
\begin{aligned}
S(J, I) = \quad &\max \left\{ 0, E[y_{i,j}] - z + \beta(1 - \delta) \left[\int U(I') - U(I) dG^J(I') + \int S^+(J, I') dG^J(I') \right. \right. \\
+ \quad &\lambda_1 \left. \int \int \max\{0, S(J', I') - S(J, I')\} dG^J(I') dF(J') \right] - \beta \lambda_0 \int S^+(J', I) dF(J') \right\}
\end{aligned}
$$

where $S^+(J, I) = \max\{S(J, I), 0\}$. Moreover, the worker's value of unemployment is

$$
U(I) \quad = \quad z + \beta \left(\lambda^0 \int S^+(J', I) dF(J') + U(I) \right)
$$

For a given shock distributions G^J, firm distribution $F(J)$ and the belief updating equations, the surplus equation can be solved. Given a solution to the surplus equation, transitions between labor states can be simulated. In this baseline case, given the contracting assumption, wages are just equal to expected output.

$$
W(J, I) \quad = \quad E[y_{i,j}]
$$

4.3 Mechanism

In this baseline model, wage growth is driven uniquely by changes in beliefs. The variance of changes in beliefs evolves deterministically as a decreasing function of labor market experience alone and approaches zero in the limit (cf. Appendix 6.7 for details). It follows that the variance of wage changes approaches zero as experience increases.

Moreover, as workers ascend on the job ladder by moving to higher quality matches, the likelihood of moving also decreases with experience. To see that, recall that in this model the ranking of firms is constant for all workers due to linearity of the production framework. Hence, the arrival of random job offers at a fixed rate implies that the likelihood of the

arrival of higher valued job offers declines as agents move up the job ladder.[14] Thereby, the model creates a coincidence of learning and moving that has the potential to create a U-shape result in the data.

In so far as tenure summarizes the time since unemployment for some workers, tenure has predictive power for separations in this framework. As layed-off workers fall from the job ladder, they restart their search for the best firm after re-entering the labor market. This is a general feature of models with on-the-job search and a job ladder. Notice further that this result is consistent with the finding in the empirical section where I document a negative effect of tenure on the U-shape result.

In the following, I will show that the baseline model can produce a U-shape pattern in a simple calibration exercise.

4.4 Calibration Baseline Model

The baseline model is defined by the set of parameters as collected in table 3. Specifically, to span the space of firm types, I use a grid on a log-normal distribution for firm productivity μ_j with mean and variance $E[\mu_j], \text{Var}[\mu_j]$. Furthermore, I span a grid of intrinsic individual types a_i using a normal distribution with mean $E[a_i]$ and variance $\text{Var}[a_i]$. I allow the distribution of initial beliefs, set up as a normal distribution with mean $E[a_i]$ and variance $\text{Var}(A_0)$, to differ from the true distribution of types in its variance. In addition, the model features the offer arrival rates λ_1 and λ_0 for an employed and unemployed worker, respectively. Finally, the model defines the spontaneous layoff rate δ.

To conform with the empirical data, I set one time period to span a year. I do not calibrate z, the flow value of unemployment, but set it to .5 as in Jarosch (2014). I set the interest rate to 5%. Moreover, in this model the standard relation $u\lambda_0 = (1-u)\delta$ between δ, λ_0 and the aggregate unemployment rate u holds for high experience agents. As endogenous layoffs only occur as a result of changes in beliefs about ability, I can take λ_0 out of the calibration exercise by targeting the separation rate of highly experienced workers together with their unemployment rate. Specifically, I target the mean aggregate unemployment rate of male workers during the 1980s of 6.6% as reported in Mazzocchi (1981).

I calibrate the eight parameters to fit a set of moments as described in table 4. First, I

---

[14]Differently put, firm quality is a function of experience in the model. This also corresponds to a steady state analogue to the measurement of match quality as in Hagedorn and Manovskii (2013).

Parameter	Description
Productivity and Types	
$E[\mu_j], \mathrm{Var}[\mu_j]$ (Log-Normal Distr.)	Marg. Dist. Firm Prod.
σ_j	Prod. Shock Volatility
$\mathrm{Var}[A_0]$ (Var. Normal Distr.)	Var. Initial Belief Ability
$E[a_i],\ \mathrm{Var}[a_i]$ (Normal Distr.)	Dist. True Ability
Labor Market	
λ^1	Offer Arrival Rate Empl.
δ	Spontaneous Layoff Rate
λ^0	Offer Arrival Rate Unempl.
Other	
r	Interest Rate $\beta = 1/(1+r)$
z	Unemployment Flow

Table 3: Parameters

target the variance of wage changes $\hat{\sigma}(\Delta W_{t-1})$. In the baseline model, the variance of wage changes at a given experience level is a function of the initial variance of beliefs $\mathrm{Var}[A_0]$, the true variance of abilities $\mathrm{Var}[a_i]$ and the variance of productivity shocks σ_j^2 (cf. Appendix 6.7). Empirically, I obtain the standard deviation of wage changes as

$$\hat{\sigma}(\Delta W_{t-1}) = \left(\frac{1}{N-1} \sum^{N} (\Delta W_{t-1} - \hat{\mu}(\Delta W_{t-1}))^2 \right)^{1/2}$$

Moreover, I target the sample standard deviation of wages $\hat{\sigma}(W_{t-1})$ and the sample standard deviation of wages for young agents at experience level of four years $\hat{\sigma}(W_{t-1})_{X=4}$. Further, I aim at fitting the skewness of wage changes $E(\Delta W_{t-1})^3$ and wages $E(W_{t-1})^3$.[15] These moments inform the belief variances as well as the firm type distribution. Furthermore, I target the ratio of the unemployment benefit and the mean wage rate $z/\mu(W_{t-1})$ to fit the replacement rate for single average wage earners without children for the year 2001 (cf. OECD). This allows me to capture the average productivities.

Finally, I choose to target the average separation rate as well as the separation rate for experienced agents with 16 years of experience. The empirical counterpart for experienced

---

[15]These are obtained, as standard, as

$$\hat{\sigma}(W_{t-1}) \;\;=\;\; \left(\frac{1}{N-1} \sum^{N} (W_{t-1} - \hat{\mu}(W_{t-1}))^2 \right)^{1/2} \quad E(W)^3 = \frac{\frac{1}{N} \sum^{N} (W_{t-1} - \hat{\mu}(W_{t-1}))^3}{\left(\frac{1}{N-1} \sum^{N} (W_{t-1} - \hat{\mu}(W_{t-1}))^2 \right)^{1/3}}$$

agents is obtained as

$$\hat{\mu}(\text{Sep})_{X=16} = \frac{1}{N} \sum^{N} \text{Sep}_{t,X=16}$$

As more experienced workers do not face endogenous separations in the model and are assumed to have reached a high rank on the job ladder, the latter separation rate allows to target δ whereas the former allows to also target λ_1. I further target the average years of tenure. Table 6 summarizes the empirical and simulated moments. Table 5 collects the calibrated parameters. The calibrated job finding rates are higher in levels than the estimates

#	Moment	Description	Data (IT)	Model
1	$\hat{\mu}(\text{Ten.})$	Mean Tenure (Years)	6.9	6.4
2	$E(W_{t-1})^3$	Skewness W	0.7	0.9
3	$E(\Delta W_{t-1})^3$	Skewness ΔW	0.5	0.5
4	$\hat{\sigma}(\Delta W_{t-1})$	Std. $\Delta W \times 100$	6.9	6.1
5	$\hat{\sigma}(W_{t-1})$	Std. $W \times 10$	3.4	3.4
6	$\hat{\sigma}(W_{t-1})_{X=4}$	Std. W Exp. 4×10	3.2	2.7
7	$\hat{\mu}(\text{Sep})$	Mean Sep. Rate %	11.9	10.2
8	$\hat{\mu}(\text{Sep})_{X=16}$	Mean Sep. Rate Exp. 16 %	8.2	8.2
9	$z/\mu(W_{t-1})$	Replacement Rate %	50	49

Exp. denotes years of experience

Table 4: Moments I

Parameter	Description	Value
	Productivity and Types	
$E[\mu_j], \text{Var}[\mu_j]$ (Log-Normal Distr.)	Marg. Dist. Firm Prod.	[.010, .0028]
σ^2	Volatility Shocks	.0153
$\text{Var}[A_0]$	Variance Initial Belief Ability	.14
$E[a_i], \text{Var}[a_i]$ (Normal Distr.)	Dist. True Ability	[.60, .14]
	Labor Market	
λ^1	Offer Arrival Rate Empl.	0.19
δ	Spontaneous Layoff Rate	0.049
λ^0	Offer Arrival Rate Unempl.	0.26
	Other	
r	Interest Rate $\beta = 1/(1+r)$	5%
z	Unemployment Flow	0.5

Table 5: Parameters

found for instance in Jarosch (2014), yet their ratio is almost identical with the one obtained

in Jarosch (2014). This could suggest an impact of the sample selection of young workers on the parameter value.

Using the calibrated parameters, I simulate 25 years of labor market histories for 2 Million workers. I then compute figure 7 in which I compare the empirical data for Italy with the simulated values. The figure recalls the empirical pattern, yet the model has difficulties to capture the variance of wage changes.
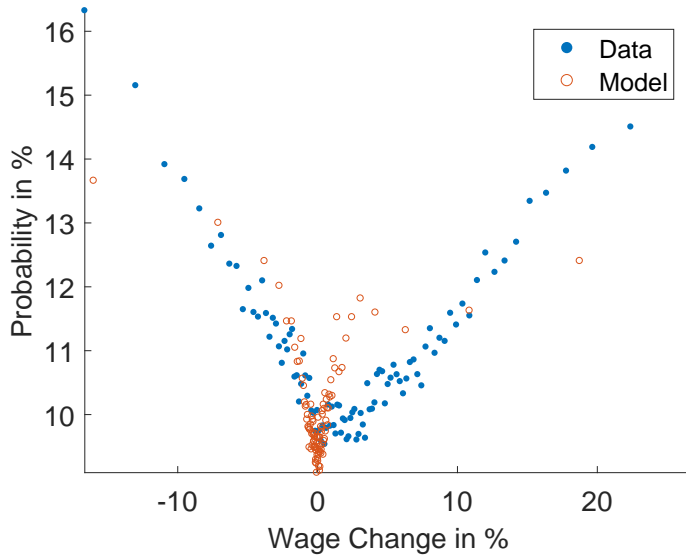

Figure 7: Data and Simulation

The figure shows the empirical U-shape in blue together with the simulated U-shape in orange overlayed. Simulations have been performed for 25 years and 2M Workers.

In the following section, I will introduce quantitative extensions aimed at bringing this baseline model closer to the data.

4.5 Quantitative Extensions

Even if the baseline model can illuminate the core mechanisms, it fares poorly in a quantitative exercise relative to two key characteristics of the empirical wage change distribution. First, the baseline model has difficulties capturing the slow decline of the variance of wage changes with experience. Moreover, the model-implied autocovariance of wage changes is zero due to the martingale property of changes in beliefs. Yet, in the data the autocovariance is consistently negative. To capture these aspects of the data, I extend the model in three dimensions. First, I allow for dynamic match productivity. Second, I introduce surplus sharing between workers and firms and let workers re-bargain their surplus share after receiving

outside offers. Finally, I allow firms to differ in both productivity and production shock volatility. I detail these aspects in the following and discuss their impact on the distribution of wage changes and separations.

4.5.1 Dynamic Match Productivity

First, I introduce unobserved dynamic match-specific productivity $n_{i,j,t}$ and assume that it enters log production additively. Specifically, I assume that $n_{i,j,t}$ follows an AR(1) structure with autocorrelation parameter ρ.

$$
\begin{aligned}
y_{i,j,t} &= \mu_j + a_i + n_{i,j,t} \\
n_{i,j,t} &= \rho n_{i,j,t-1} + \epsilon_{i,j,t}
\end{aligned}
$$

As an experience good, I assume initial match productivity at a new spell to be zero. In the following, I denote the belief about dynamic match productivity with N_t and denote the match-specific state vector as $M = \{N_{t-1}, I_{OTJ}\}$, where I_{OTJ} is an indicator function equaling 1 after the first year of tenure. The latter is required in the updating formula due to initial match productivity being zero.

Autocorrelation in match-specific productivity changes the learning process slightly (cf. Appendix 6.6). First of all, the speed of learning will depend on the autocorrelation of match-specific productivity. For instance, if match productivity was a random walk, there would be no learning and the precision of the belief about ability would be constant in time. Secondly, wage growth will be driven by changes in beliefs and innovations to match specific productivity. In the absence of surplus sharing, wage changes equal changes in realized dynamic match productivity such that

$$
\Delta W_t = \Delta A_t + \Delta N_t = \Delta n_t
$$

(cf. Appendix section 6.8 for details). This implies that the variance of wage changes and the autocovariance of wage changes are a direct function of the variance of shocks to dynamic productivity and of the autocovariance of match productivity.[16] This setting hence allows for a negative autocorrelation of wage changes.

---

[16]Specifically, in this case I obtain for the variance of changes in wages $\text{Var}(\Delta W_t)$ and the autocovariance of wage changes at the first lag $\gamma(1)$

$$
\text{Var}(\Delta W_t) = \frac{2\sigma_J^2}{1+\rho} \qquad\qquad \gamma(1) = \frac{-\sigma_j^2(1-\rho)}{1+\rho}
$$

However, the extension does not only alter the wage distribution but also affects separations in the model. Given the known initialization of match productivity at new spells, negative productivity shocks can lead to separations in the model.

4.5.2 Wage Renegotiation

Secondly, I allow for renegotiation of wages in the spirit of Postel-Vinay and Robin (2002). Specifically, I will assume that the bargaining schedule is fixed such that a worker always receives the surplus at his outside option plus a share α of the difference between the surplus at the current match and his outside option. Moreover, workers matching out of unemployment have an outside option of zero. In the following I track worker's outside options in vector $O = \{\mu^o\}$. Specifically, the worker's surplus equals

$$W(J, I, O, M) - U(I) = S(O, I, M^0) + \alpha(S(J, I, M) - S(O, I, M^0))$$

Allowing for dynamic surplus sharing between firm and workers introduces the firm problem and alters the surplus and the wage equations, which are collected in Appendix section 6.5. The surplus of worker I at firm J with current match productivity M is then

$$
\begin{aligned}
S(J, I, M) \ = \ \max \Bigg\{ & 0, E[y_{i,j}] - z + \beta(1 - \delta)\Bigg[\int U(I') - U(I) dG^J(I') \\
& + \ \lambda_1 \int_{\mathcal{M}_2} \int_{\mathcal{M}_1} \alpha(S(J', I', M^0) - S(J, I', M^0)) dG^J(I') dF(J') \\
& + \ \lambda_1 \int_{\mathcal{M}_2} (S(J, I', M^0) - S(J, I', M')) dG^J(I') dF(J') \\
& + \ \int S^+(J, I', M') dG^J(I') \Bigg] - \beta\alpha\lambda_0 \int S^+(J', I, M^0) dF(J') \Bigg\}
\end{aligned}
$$

where $\mathcal{M}_1 : \{S(J', I', M^0) > S(J, I', M')\}$ and $\mathcal{M}_2 : \{S(J, I', M') > 0\}$ denote the set of matches in which a worker moves to a new firm and in which the match pertains after updating, respectively.

To consider the impact of the surplus sharing rule on the distribution of wage changes, consider two polar cases: one in which all surplus is reaped by the worker ($\alpha = 1$) and one in which all surplus is given to the firm ($\alpha = 0$). The former case corresponds to the sharing rule in the baseline model and it continues to hold that wage changes will equal changes in expected output in this case. In the latter case, the worker receives the surplus at his outside option such that wage changes only reflect changes in beliefs about ability

and on-the-job wage renegotiation. This difference implies that variations in the bargaining weight will determine the extend to which workers can insure against match specific productivity shocks by searching for outside options. Differently put, outside options do not only affect the level of wages that workers receive, they also allow to lower the variance of wage changes due to match specific productivity at the current employer. To see that, consider the case of a worker matching with a firm out of unemployment. This worker obtains the surplus share $W(J, I, 0, M^0) - U(I) = \alpha S(J, I, M^0)$. This worker's wage will reflect all changes in the surplus due to changes in beliefs about match specific productivity and ability. On the other hand, consider a worker that meets a firm with productivity ϵ away from his current employer. This worker can renegotiate his surplus share to $W(\mu_j, I, \mu_j - \epsilon, M) - U(I) = S(\mu_j - \epsilon, I, M^0) + \alpha(S(\mu_j, I, M) - S(\mu_j - \epsilon, I, M^0))$. At low values of α, the worker's wage varies few with match specific productivity. However, high levels of a worker's surplus share imply that workers cannot evade earnings instability due to match specific productivity. As a result, this extension contributes to the mechanism by increasing the variance of on-the-job wage changes due to an additional channel for wage growth, but also by increasing the variance of wage changes for agents at low ranks of the job ladder as compared to agents with outside options. The experience effect is therefore potentially reinforced through the bargaining schedule.

Even though this extension changes the distribution of wage changes in the model, it leaves the ranking of firms unaltered and therefore does not affect separation decisions. This is important in that it potentially requires a lower variance of firm shocks to fit the empirical wage change distribution.

4.5.3   Firm Types

Finally, I extend the firm space by allowing firms to differ additionally with respect to their shock volatility, denoted by σ_j^2. The firm state vector now contains two elements $J = \{\mu_j, \sigma_j^2\}$. I parameterize the distribution of the production shock volatility with a log-normal distribution with mean $E[\sigma_j^2]$, $\text{Var}[\sigma_j^2]$ and allow the two firm characteristics to be correlated in sample through the correlation parameter ρ_1.

This extension contributes to the modeling of the experience profile of the variance of wage changes. First, if high productive firms are more likely to feature low productivity shock variances, the experience effect of the U-shape is reinforced. Secondly, as the precision of the belief about the worker's type decreases in the variance of match-specific productivity shocks, the variance of wage changes is further reduced at high productive firms in this sce-

nario. Moreover, allowing for match specific productivity, in combination with firms differing in shock volatilities, allows for a U-shape result that is not related to learning. To see this, assume that low productive firms are equally highly volatile firms. As a consequence there could be a coincidence of a high wage change variance and a high endogenous separation propensity. Note that the required correlation between firm productivity and volatility needs to be negative in sample for this channel to be operative.

4.6   Calibration Extended Model

Compared to the baseline model, these extensions widen the parameter space by four additional parameters, namely the variance of the variance of productivity shocks $\text{Var}[\sigma_j]$, the autocorrelation parameter of dynamic match productivity ρ, the sample correlation between firm characteristics ρ_1 and the worker's bargaining weight α. As before, I calibrate the model internally to match a set of simulated moments except for the discount rate and the unemployment benefit. In the following, I give a heuristic description of the relationship between the targeted moments and the additional parameters, including differences that arise in the extended model.

Differently from the baseline model, the standard deviation of wage changes $\hat{\sigma}(\Delta W_{t-1})$ in the full model is now a function of the variance of changes in dynamic match productivity (as explained in the previous section), such that $\hat{\sigma}(\Delta W_{t-1})$ targets the distribution of the variance of production shock volatilities and the persistence of match productivity ρ. Given that wage bargaining allows to lower the wage change variance through outside options, $\hat{\sigma}(\Delta W_{t-1})$ also depends on the distribution of firm types, the job finding rate and the wage bargaining weight α. In addition to the unconditional standard deviation of wage changes $\hat{\sigma}(\Delta W_{t-1})$, I also target the standard deviation at experience of 4 years $\hat{\sigma}(\Delta W_{t-1})_{X=4}$ to capture the experience profile of wage changes.

To inform the estimate of the autocorrelation of dynamic match productivity ρ, I further compute the autocorrelation of wage changes at the first lag at experience of 16 years $\hat{\gamma}(1)_{\Delta W_{x=16}}$.[17] Finally, to target α as well as the firm type distribution, I also aim at capturing the ratio of the wage of workers just out of unemployment to the average wage $\mu(W_{t-1}^0)\hat{/}\mu(W_{t-1})$ as well as the labor share, defined as the ratio of the sum of wages to

---

[17]The sample analogue is obtained as

$$(\hat{\gamma}(1)_{\Delta W})_{x=16} = \frac{\sum^{N-1}(\Delta W_{t-1,x=15} - \hat{\mu}(\Delta W_{t-1,x=15}))(\Delta W_{t,x=16} - \hat{\mu}(\Delta W_{t,x=16}))}{\sum^{N}(\Delta W_{t,x=16} - \hat{\mu}(\Delta W_{t,x=16}))^2}$$

output $ls = \sum W_{i,j,t} / \sum y_{i,j,t}$. I compute $\widehat{\mu(W^0_{t-1})}/\mu W_{t-1}$ as

$$\widehat{\mu(W^0_{t-1})}/\mu W_{t-1} = \frac{\frac{1}{N^o} \sum^{N^o} W_{t-1,o}}{\frac{1}{N} \sum^N W_{t-1}}$$

The empirical set of moments is collected in table 6. There is a total number of 13 moments for a set of 13 parameters. None of these moments directly targets the U-shape. However, by imposing an experience profile on separations and the variance of wage growth, the moments target the mechanism in the model. Moreover, the moments specifically aim at targeting differences in the exposure of agents to match-specific shocks due to the job ladder and wage renegotiation. Results for the calibration of the full model are reported

#	Moment	Description	Data	Model Baseline	All
1	$\hat{\mu}(\text{Ten.})$	Mean Tenure (Years)	6.9	6.4	6.7
2	$E(W_{t-1})^3$	Skewness W OJ	0.7	0.9	0.7
3	$E(\Delta W_{t-1})^3$	Skewness ΔW OJ	0.5	0.5	0.5
4	$\hat{\sigma}(\Delta W_{t-1})$	Std. ΔW OJ $\times$ 100	6.9	6.1	7.1
5	$\hat{\sigma}(W_{t-1})$	Std. $W \times 10$	3.4	3.4	3.5
6	$\hat{\sigma}(W)_{X=4}$	Std. W Exp. 4 $\times$ 10	3.2	2.7	2.7
7	$\hat{\mu}(\text{Sep})$	Mean Sep. Rate %	11.9	10.2	10.5
8	$\hat{\mu}(\text{Sep})_{X=16}$	Mean Sep. Rate Exp. 16 %	8.2	8.2	8.5
9	$z/\mu(W)$	Replacement Rate %	50	49	48
		Targeted Only in Model (All)			
10	$\hat{\gamma}(1)(\Delta W_{t-1})_{X=16}$	AutoCorr. Exp. 16	-0.20		-0.20
11	$\widehat{\mu(W^0_{t-1})}/\mu W_{t-1}$	Wage Ratio out of Unemp.	0.87		0.81
12	$\hat{\sigma}(\Delta W_{t-1})_{X=4}$	Std. W Exp. 4 $\times$ 100	7.6		6.0
13	$\hat{ls}$	Labor Share %	40		39

Exp. denotes years of experience, Ten. years of tenure

Table 6: Moments I

in table 7. Compared to the literature, I find again a high value of the offer arrival rates. The high parameter value for $\text{Var}[A_0]$ shows that learning is an active mechanism in the calibrated version of the model. Moreover, the autocorrelation parameter ρ is not too high and the correlation of firm attributes in sample ρ_1 is negative. Given that the correlation of firm attributes is negative in the model, we find that the U-shape pattern is amplified by low quality firms being more volatile. Moreover, I find a high level for the worker surplus share, reflecting the high volatility of wage changes. As a low value of α implies less expose of workers to match specific productivity shocks, the calibration shows a high level of risk exposure. Overall, the fit of the model to the U-shape is improved, as can be seen in figure 8. The better fit of the variance of wage changes reflects in a less narrow pattern.

Parameter	Description	
Productivity and Types		
$E[\mu_j], \text{Var}[\mu_j]$ (Log-Normal Distr.)	Marg. Dist. Firm Prod.	[-0.10 0.008]
$E[\sigma_j], \text{Var}[\sigma_j]$ (Log-Normal Distr.)	Marg. Distr. Volatility	[-3.52 0.01]
ρ_1	Corr. Firm Attributes σ_j, μ_j	-0.89
ρ	Persistence Firm Shocks	0.22
$\text{Var}[A_0]$	Var. Initial Belief Ability	0.48
$E[a_i], \text{Var}[a_i]$ (Normal Distr.)	Dist. True Ability	[1.11 0.24]
Labor Market		
λ^1	Offer Arrival Rate Empl.	0.33
δ	Spontaneous Layoff Rate	0.029
α	Worker Bargaining Weight	0.86
λ^0	Offer Arrival Rate Unempl.	0.45
Other		
r	Interest Rate $\beta = 1/(1+r)$	5%
z	Unemployment Flow	.5

Table 7: Parameters
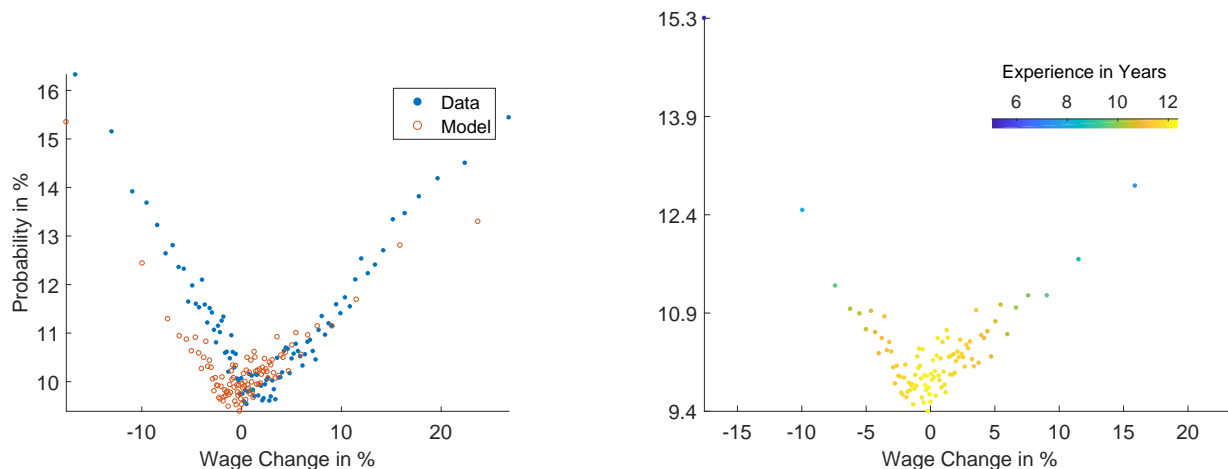
Figure 8: Simulated Data and Data (Italy)

The left figure shows the empirical U-shape in blue together with the simulated U-shape in orange overlayed. On the right, I show the simulated U-shape and color-code the dots for their mean experience level.

To gauge the impact of the parameters on the U-shape pattern, I simulate the model by deviating from the calibrated parameters in three ways (while leaving all other parameters unchanged). First, I switch off learning and set $\sigma_{a0} = 0$. I then allow for a positive sample correlation between productivity and volatility at $\rho_1 = 0.89$. Finally, I set a high autocorrelation of the persistence of productivity shocks, such that $\rho = 0.7$.
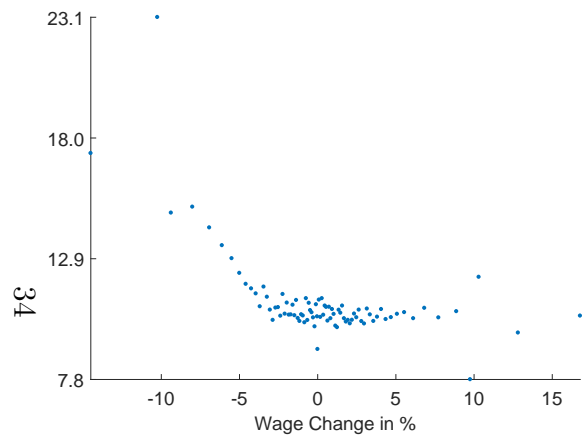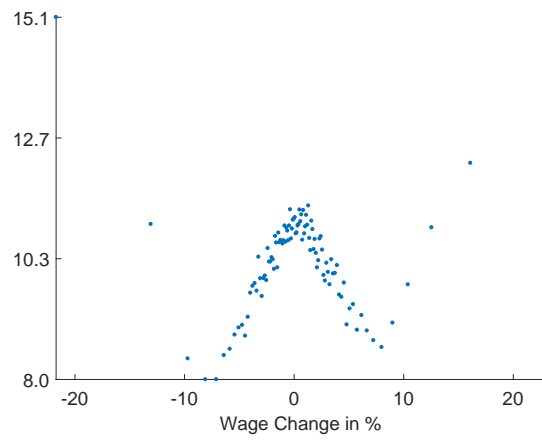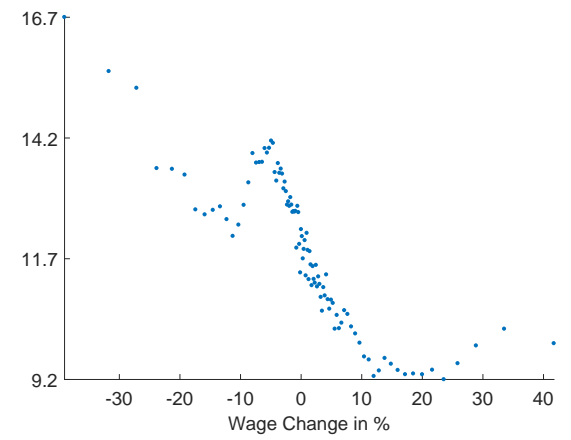
Figure 9: Adjusting the Parameter Space

The three figures show the U-shape between wage changes and separations for three simulations. Each simulation changes one parameter at a time while fixing the remaining parameters.

The effect of these changes is significant. First, switching off learning removes the upward sloping part of the U-shape, as can be seen in panel (a) of figure 9. In this setting, positive wage growth is driven by either match-productivity or renegotiation, yet none of these cases lets expect an increase in the separation. This figure hence shows that the right-hand side of the U-shape is in fact the result of learning in the model. Second, a change in the sample correlation between firm characteristics can revert the (core) U-shape to create a W pattern. In this version of the model, workers at high volatile firms on average benefit from high productivity, such that high volatility of wage changes due to dynamic match productivity is correlated with a low propensity to separate. In this model, the largest wage changes are still due to learning of young agents and thus separation rates at the edges of the distribution are high. Therefore, a U-shape pattern requires a low in-sample correlation between firm productivity and production shock volatility. This implies that firms that pay higher wages are also those with lower volatility and therefore lower risk of endogeneous separations. It also implies that workers on low levels of the job ladder face both higher volatility of income, higher risk of endogenous separation and lower earnings. This is in line with the finding of Jarosch (2014) of better jobs offering more job stability. [18] Finally, increasing the persistence of productivity shocks can lead to a downward sloping curve. This result is also intuitive; with high enough persistence, good productivity shocks can partially insure workers against future shocks and hence reduce separations after a positive shock. Therefore, the right hand side of the figure is subdued. The existence of a U-shape thus requires job-specific dynamic components of wages not to be too persistent. This further shows that the model can deliver both a downward sloping and a non-monotone relationship between wage changes and separations.

In summary, the calibration exercise has shown that the model can fit the U-shape pattern in the data and that learning is a crucial component of the U-shape in this calibration. Hence the U-shape is not dominantly driven by differences in volatility and endogenous separation rates across firms. Moreover, the firm type distribution is vital in supporting the pattern.

Notice that this paper has given one possible interpretation to the autocorrelated part of productivity as dynamic match productivity and to variations in the volatility of beliefs about productivity as learning. Yet other interpretations of match productivity as exogenous relative price fluctuations or learning of skills at the job are possible. Reversely, variations in

---

[18] Jun and Munasinghe (2005) show for the US NLSY that young workers quitting from more volatile jobs receive larger wage gains. This is consistent with a job ladder in which low quality jobs are on average more volatile.

the volatility of beliefs about productivity could in fact represent a learning technology of general skills with declining variance. This result suggest therefore that spell-specific dynamic components of productivity growth cannot be too strong and early career volatility in fixed factors cannot be too small for a U-shape pattern to exist in the data. Notice that this implies that inexperienced workers have only a small margin to insure themselves against future negative spell-specific productivity shocks at low productivity firms.

4.7 Implications

In the following, I discuss two implications of the model. They describe driving forces of the decline of the variance of wage changes with experience, namely the firm type distribution and surplus renegotiation. The second implication further discuss how the exposure of workers to productivity shocks varies with experience. Specifically, I first show that in the calibrated model, a significant fraction of the decline in the variance of wage changes due to experience is a result of the firm type distribution. Second, I show that wage renegotiation allows for partial insurance of workers against match-specific productivity shocks, while also increasing exposure to changes in beliefs about worker's ability. Therefore, the model predicts different experience paths for the variance of wage changes for workers with high and low negotiation capital, overall reinforcing the decline of the variance of wage changes at high experience levels.

4.7.1 The effect of the firm type distribution

In the model, the job ladder affects separations and the volatility of wage changes simultaneously. First, the job ladder induces workers to switch from low to high productive firms. Second, the job ladder allows to reduce wage change volatility due to match specific productivity through the accumulation of renegotiation capital. The decline in wage change volatility is reinforced by an uneven distribution of production shock volatility along the job ladder. Movements along the job ladder hence reduce both volatility of wage changes and the likelihood of separations. To quantity these effects in the calibrated model, I decompose the variance of wage changes in the model into the effect due to learning about the ability of a worker, the effect due to match specific shocks in the presence of insurance through the job ladder, and finally the variance of wage changes after allowing for differences in the firm type distribution. In Figure 10, I show the experience profile for the standard deviation of wage changes and for wages in the calibration discussed above and in the data. Moreover, I show how the different channels in the model contribute to the time profile. First, I switch off surplus sharing between the worker and the firm ($\alpha = 1$). In the calibrated model, the value for the workers bargaining weight is very high, so that this alteration barely changes
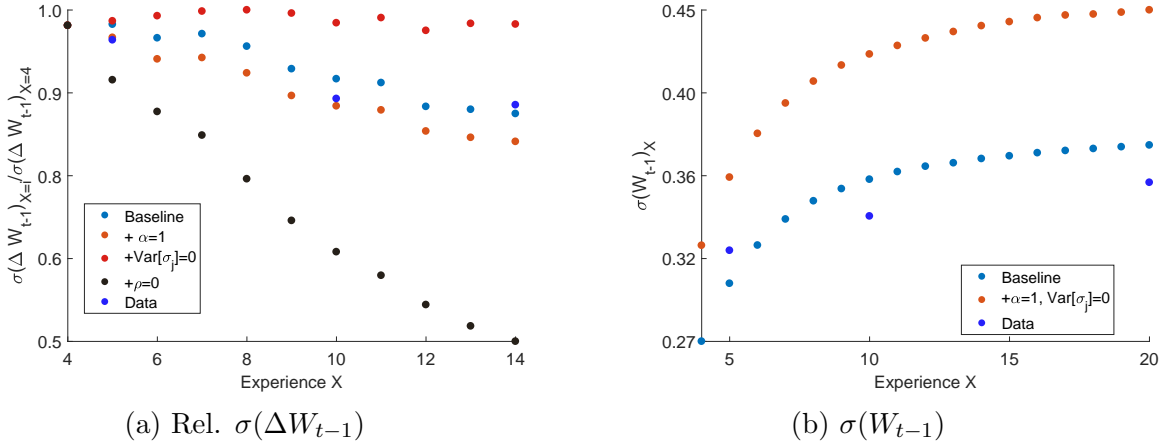
Figure 10: Experience Profile ΔW_{t-1} and W_{t-1}

The left figure shows the ratio of $\sigma(\Delta W_{t-1})$ at experience level X relative to the value at experience level 3 for four simulations as well as the data. The right hand figure shows the corresponding variance path $\sigma(W_{t-1})$ for two simulations and the data.

the time path for the standard deviation of wage changes. Second, I impose homogeneity in the volatility of productivity shocks across firms. Given that the variance of wage changes is equal to the variance of match specific productivity (due to linearity of the production framework and unity of the bargaining weight), this case leads to a flat variance profile of wage changes. Finally, I impose zero serial correlation in match specific productivity. In this version, the model is equal to the simple model version that only features learning. The figure shows that both serial correlation of productivity shocks and heterogeneous firm variances rationalize the time path in the data. Specifically, heterogeneous firm variances allow for the majority of the decline of the variance profile in the model. [19]

4.7.2 Variable exposure to productivity shocks through renegotiation

In the model, workers that accumulate outside offers do not only increase their wages, they also affect the variability of their income. This is due to the contracting rule through which the surplus value at the outside option is independent of match specific shocks, yet the surplus value at the firm varies with changes in beliefs about ability. Hence, the effect of outside options for the variability of wages varies as agents accumulate experience.

To show the effect of this mechanism in the model, I compute the experience profile for

---

[19]Notice that this conclusion is driven in part by linearity of the production framework and the high surplus weight of the worker. By allowing for multiplicative production, for instance, the precision of beliefs is a function of firm productivity as well and it does not hold that changes in wages equal changes in match specific productivity. Hence the firm type distribution would carry less weight in such a framework.

the variance of wage changes for agents that do not have outside options and those that could raise their effective surplus share $\hat{\alpha}$ above α, where $\hat{\alpha} = \alpha + (1-\alpha)S(O,I)/S(J,I)$ and O denotes the current outside option. Figure 11 shows that low experience workers without
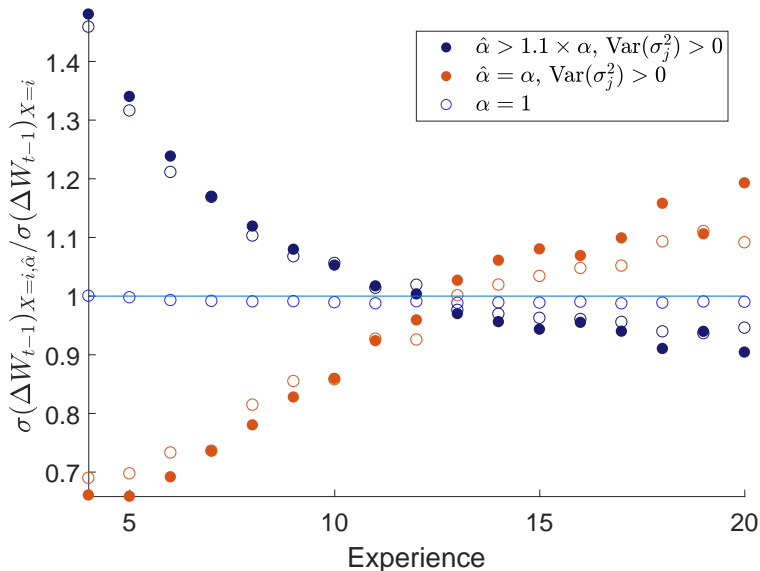
Figure 11: Experience Profile Rel. $\sigma(\Delta W_{t-1})$

The figure shows the ratio of $\sigma(\Delta W_{t-1})$ at experience level X for a given $\hat{\alpha}$ relative to the unconditional value of $\sigma(\Delta W_{t-1})$ at experience level X. Hollow dots represent simulations in which $\mathrm{Var}(\sigma_j^2) = 0$.

outside offers have in fact lower and workers with outside options indeed higher variability of wage changes. Precisely, workers with 5 years of experience and without outside offers have about 30% less variability in their wage changes than the average worker at the same experience level and workers with at least a 10% higher effective surplus share (or $\alpha \geq .947$) have about 50 % higher variability. This implies that the decline of the variability of wage changes with experience is also driven by the accumulation of outside offers.

This effect is not driven by the firm type distribution as can be seen by the hollow dots representing simulations in which I do not allow firms to differ wth respect to their production shock volatility $\mathrm{Var}(\sigma_j^2) = 0$. For comparison, I also show the experience profile that would pertain in the absence of surplus sharing ($\alpha = 1$). In this case, workers cannot reduce their exposure to match specific productivity shocks nor new information about their own ability.

This result is in line with empirical findings in the literature showing that experienced workers are less exposed to firm-specific shocks than young workers (cf. Davis and Wachter (2011)). Moreover, this result is also consistent with empirical evidence for the US that experienced displaced workers face higher income instability up to several years after the displacement (cf. Stevens (2001)). Recall that workers falling off the job ladder through

displacement loose all negotiation capital, such that their future exposition to match-specific shocks will increase.

4.8   Application: Decentralizing Wage Negotiations

In this section, I use the model to study the effect of a change in the worker's surplus share and its implications for wage variability.

In the model, a change in the worker's surplus share reduces initial wages at the job while still allowing for wage progression through the accumulation of outside offers. A change in the surplus share hence corresponds most closely to a decentralization of wage determination, as has been observed in a number of advanced economies. Empirically, a large literature has shown that the decline of unionization increased wage dispersion in a number of countries (cf. among others Card (2001), DiNardo et al. (1996), Card et al. (2003)). Specifically for Italy, the decline of the wage indexation mechanism *Scala Mobile* has been shown to contribute to an increase in inequality among workers (Manacorda (2004)).

Despite pervasive research of the effect of decentralized wage determination on wage dispersion, to the best of my knowledge no research has discussed its effect on the instability of wages. This model allows to trace changes in wage instability as a result of changes in the bargaining schedule and to differentiate the effect for different groups of workers. In the following, I will study workers at different experience levels with or without negotiation capital. Specifically, I will show that wage inequality within groups of workers with and without negotiation capital falls, yet wage inequality between these groups rises. Finally, I will show that wage instability falls for workers with negotiation capital but rise for those without. Hence, a fall in the surplus share of workers increases the variability of wages above all for young or displaced workers.

In the following, I will study the effect of a decline of the worker's bargaining weight by 14%, equivalent to a fall in the labor share from .4 to .35. Theoretically, a falling bargaining weight reduces the exposure of workers to productivity shocks, yet it increases the variability of wages due to wage renegotiation. The resulting overall effect on the variability of wages is a quantitative question and will likely differ across workers. In the simulation in figure 12, I first show that the variance of wages increases overall, consistent with the empirical evidence. Specifically, a decline in the worker's surplus share by 14% leads to an increase in inequality across workers of 7 to 9%, cf. Figure 12, panel (a). This rise in inequality however masks declining within-group wage variances, as we can see in panel (b), where I plot the
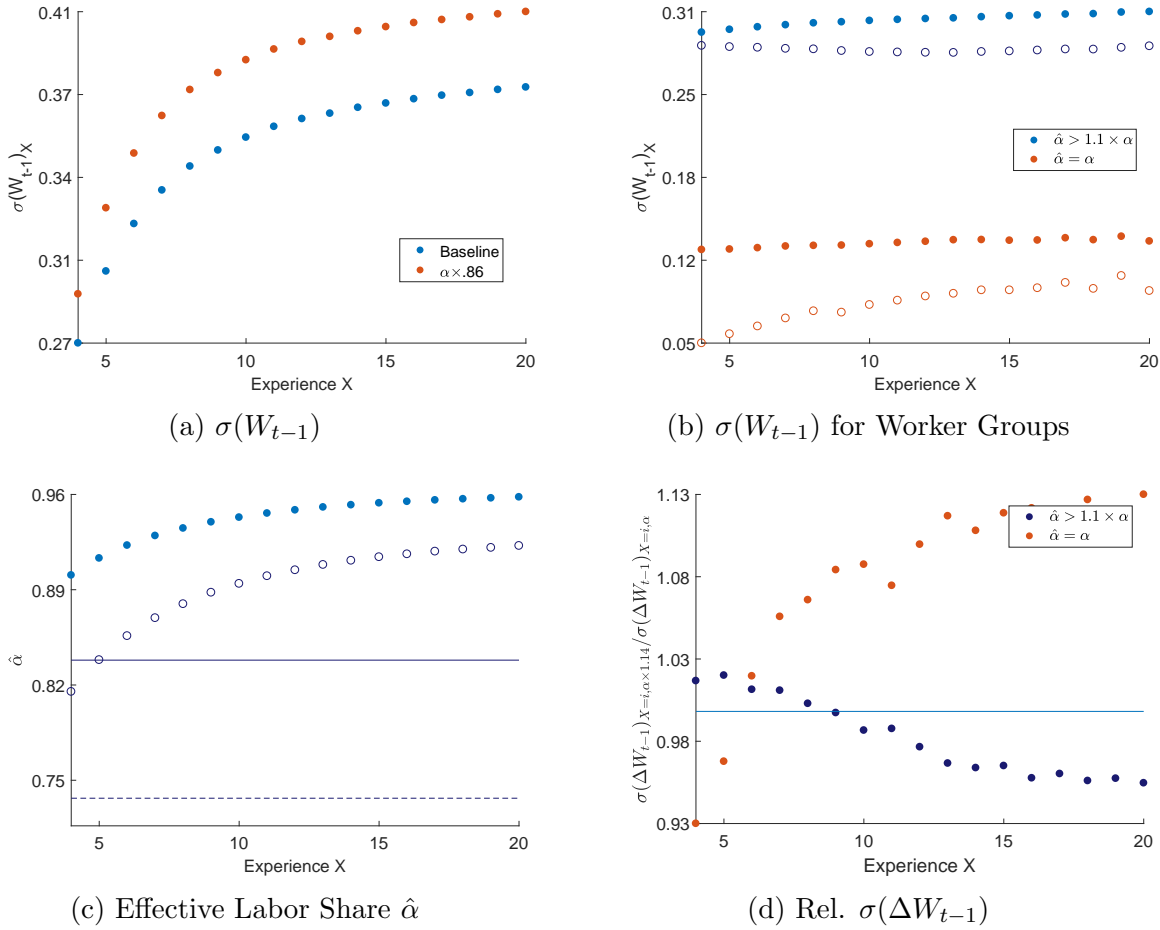
Figure 12: The effect of a decline in the worker surplus share

The figure shows the ratio of $\sigma(\Delta W_{t-1})$ at experience level X for a given $\hat{\alpha}$ relative to the unconditional value of $\sigma(\Delta W_{t-1})$ at experience level X. Hollow dots represent simulations in which $\alpha \times .86$. The right hand figure shows the corresponding variance path $\sigma(W_{t-1})$.

variance of wages for workers with and without renegotiation capital. In this figure, hollow dots represent the case with low worker surplus share. The variance of wages falls for both groups of agents after a fall in the surplus share. This fact mirrors the different exposure to productivity shocks after the change and thereby stresses rising inequality through larger between group differences. Panel (c) shows the difference in the effective labor share for the two cases. At low levels of experience, the average effective labor share after the fall in the bargaining weight is about 10% lower than in the benchmark case, whereas at experience level over 15 years, the difference is less than 4%. The concave profile of the experience profile of wage inequality hence entirely reflects the profile for the accumulation of negotiation capital. In panel (d), I plot the standard deviation of wage changes for agents with and without negotiation capital. The figure shows that with lower bargaining weight, workers

40

without renegotiation capital face on average 7% lower variance of wage changes at low levels of experience but up to 13% higher variance at high experience levels. Workers with high bargaining weight, on the other hand, face up to 4% lower variability of wage changes. This is due to the fact that workers with high negotiation capital can reduce their exposure to match-specific productivity shocks more under low bargaining weights. Moreover, the elasticity of wages to match specific productivity shocks increases with experience (cf. last section).

To summarize, a fall in the bargaining weight reduces the exposure of both experienced and inexperienced agents to match-specific productivity shocks and thereby reduces wage variability for high experience workers with negotiation capital. Overall, inequality within groups of workers with high and low negotiation capital falls but increases between these groups, leading to a rise in inequality in the labor force. Whereas the rise of the between group variance is a feature of any model with surplus renegotiation through on-the-job search, the fall in within group variances is entirely driven by the insulation of workers to productivity shocks as discussed in this paper. This exercise has shown that decentralization of wage bargaining does not lead to a uniform increase in wage variability and wage inequality, but rather that declining wage variability and within-group inequality can coincide with a rise in aggregate inequality.

5   Conclusion

In this paper, I document a new empirical fact, that is a U-shape relationship between wage changes and the propensity of job separation. I further show that the effect is strongest for low experience workers at low quality firms. Based on this result, I propose a theoretical framework that can rationalize the U-shape pattern as the coincidence of workers' learning about themselves with the reallocation of workers on the job ladder. In the framework, labor market frictions and information frictions contribute to the U-shape pattern observed in the data.

This research shows that the job ladder does not only determine the level of wages but can also account for part of its variability. In my model, information and search frictions increase wage variability, while negotiation capital and movements along the job ladder can reduce wage variability. Bargaining frameworks determine the extend of workers' exposure to income risks throughout workers' labor market career. Specifically, decentralized bargaining settings decrease workers' wage instability while simultaneously increasing aggregate wage inequality in my model. This research hence informs policy makers about trade-offs between wage variability and income inequality of workers.

The model is amenable to incorporating occupational change. While I showed that occupational switching is not the dominant driver of the U-shape pattern, occupational switching also impacts job mobility of young agents and hence complements the perspective taken in this paper. Such an extension would allow me to capture the combined diverging and converging forces of job mobility through separations and occupational mobility. Compared to Kambourov and Manovskii (2004) who show the intimate link between wage inequality and occupational switching, separations reduce within and between firm inequality in my model. An extensive study of the effect of firm-to-firm mobility on inequality therefore needs to take into account both of those diverging and converging forces. Such an analysis is beyond the scope of this paper but I intend to explore it in the future.

6 Appendix

6.1 Summary Statistics

	Italy (1975-2001)			Germany (1993-2010)			Austria (2000-2016)		
	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median
Age	35.39	7.74	35	34.60	5.62	34	35.14	5.51	35
Tenure at the Firm	7.22	4.97	6	5.29	3.29	4	6.38	3.28	5
Labor Market Experience*	13.54	6.61	13	9.70	4.55	10	9.31	3.80	9
Size Firm	158	419	24	932	2305	195	512.81	1049.66	120
% Δ Log Real Wage	2.65	7.14	1.9	1.85	5.88	1.28	2.98	6.77	1.94
% Separations	11.0	31.29	0	16.22	36.86	0	9.24	28.96	0
Observations	2.6M			.6M			2M		

*as measured in the data set

Table 8: Summary Statistics I

	Italy (1975-2001)		Germany (1993-2010)		Austria (2000-2016)	
	Count	Mean	Count	Mean	Count	Mean
Worker	254 K		148K		40K	
Firms	28K		65K		80K	
% Manufacturing (Work.)		54.10		32.83		39.22
% Manufacturing (Firms)		47.70		15.42		21.17
% Blue Collar		71.10				
% White Collar		26.40				
% Secondary/Interm. School				68.00		
% University Degree				9.54		
Observations	2.6M		.6M		2M	

Table 9: Summary Statistics II

6.2 Tables and Figures
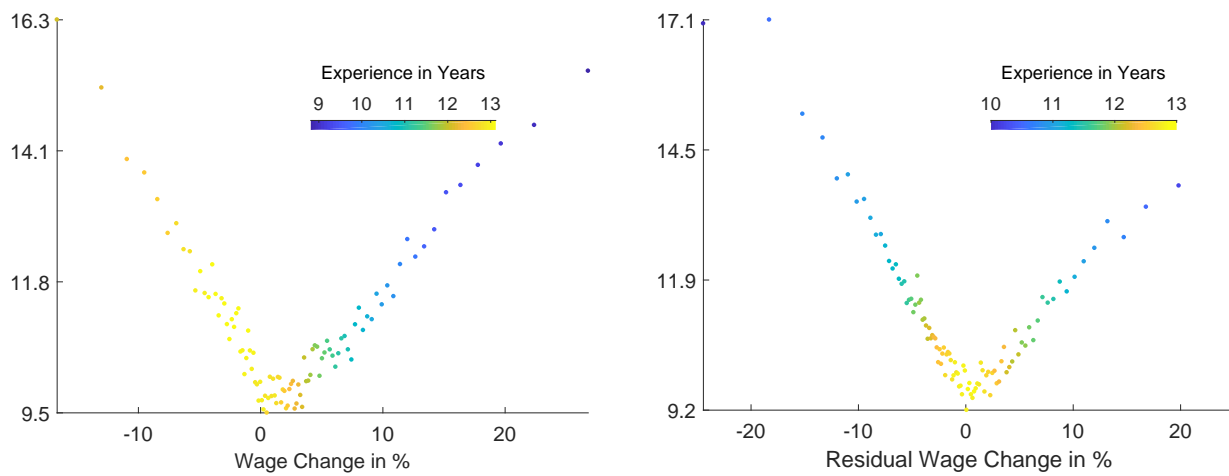
Figure 13: The U-Shape between Wage Changes and Separations (Italy)

The figure shows the average separtion rate at time t for workers experiencing wage changes at time $t-1$ within centiles of the distribution of wage changes (left panel) and within centiles of the distribution of changes in residual wages (right panel). Color coding is computed as the mean within-bin years of experience.

	Italy			Germany			Austria		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
1st Decile	1.42***	3.51***	1.57***	1.39***	4.46***	1.59***	1.30***	2.33***	1.55***
	(0.013)	(0.039)	(0.014)	(0.022)	(0.068)	(0.026)	(0.014)	(0.027)	(0.019)
2nd Decile	1.19***	1.44***	1.27***	1.24***	2.58***	1.45***	1.12***	1.38***	1.36***
	(0.011)	(0.018)	(0.012)	(0.020)	(0.041)	(0.024)	(0.012)	(0.018)	(0.017)
3th Decile	1.11***	1.08***	1.18***	1.24***	1.44***	1.41***	1.07***	1.10***	1.29***
	(0.011)	(0.014)	(0.011)	(0.020)	(0.024)	(0.023)	(0.012)	(0.015)	(0.016)
4th Decile	1.01	1	1.09***	1.20***	1.24***	1.28***	1.03**	1	1.12***
	(0.0099)	(.)	(0.011)	(0.019)	(0.022)	(0.021)	(0.012)	(.)	(0.015)
5th Decile	1.01	1.01	1.05***	1.14***	1.04	1.15***	1.04**	0.95***	1.03*
	(0.0098)	(0.014)	(0.010)	(0.018)	(0.019)	(0.020)	(0.012)	(0.013)	(0.014)
6th Decile	1	1.16***	1	1	1	1.09***	1	1.09***	1.02
	(.)	(0.015)	(.)	(.)	(.)	(0.019)	(.)	(0.015)	(0.014)
7th Decile	1.05***	1.45***	1.01	1.08***	1.07***	1.03	1.00	1.20***	1.01
	(0.010)	(0.018)	(0.0099)	(0.018)	(0.019)	(0.018)	(0.011)	(0.016)	(0.013)
8th Decile	1.09***	1.99***	1.03**	1.13***	1.03	1	1.03**	1.44***	1
	(0.010)	(0.024)	(0.010)	(0.018)	(0.019)	(.)	(0.012)	(0.018)	(.)
9th Decile	1.18***	3.16***	1.14***	1.17***	1.16***	1.08***	1.14***	2.10***	1.03*
	(0.011)	(0.036)	(0.011)	(0.019)	(0.020)	(0.019)	(0.013)	(0.025)	(0.014)
10th Decile	1.42***	8.88***	1.34***	1.38***	1.77***	1.34***	1.42***	4.47***	1.17***
	(0.013)	(0.095)	(0.013)	(0.022)	(0.029)	(0.022)	(0.015)	(0.050)	(0.015)
N	2.3M	2.3M	2.3M	.6M	.6M	.6M	1.8M	1.8M	1.5M
ΔW	$t-1$	t	Res.	$t-1$	t	Res.	$t-1$	t	Res.

Exponentiated coefficients; Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Res. denotes changes of residual wages, cf. Text for definition.

Table 10: Baseline Specification, Residual Specification and U-Shape with Wage Growth time t

	Italy			Germany				Austria			
	(a)	(b)	(c)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
ΔW_{t-1}	-0.11	-0.032	-0.045					-0.084	-0.016	-0.016	-0.074
	(0.0036)	(0.0027)	(0.0021)					(0.0044)	(0.0029)	(0.0037)	(0.0031)
ΔW^2_{t-1}	1.41	0.53	0.74					1.25	0.53	0.77	0.73
	(0.023)	(0.017)	(0.014)					(0.027)	(0.018)	(0.023)	(0.019)
Constant	0.11	0.065	0.033					0.10	0.048	0.071	0.049
	(0.00023)	(0.00018)	(0.00014)					(0.00026)	(0.00017)	(0.00022)	(0.00019)
Observations	2.3M	2.3M	2.3M	2.3M	2.3M	2.3M	2.3M	1.8M	1.8M	1.8M	1.8M

Standard errors in parentheses. All entries are significant at $p < 0.001$.

Table 11: Reasons for Separation

Column (a) contains the baseline specification for separations, column (b) contains quitts, column (c) contains layoffs in the IT sample. In DE & AT sample, column(b) contains quitters with at most 2 months of non-employment, column (c) denotes quits as constructed as a reminder after accounting for received unemployment benefits, column (d) denotes layoffs as constructed through observed receipt of benefits. See text for details. RESULTS FOR GERMANY COMING SOON (CONFIDENTIALITY CLEARING).
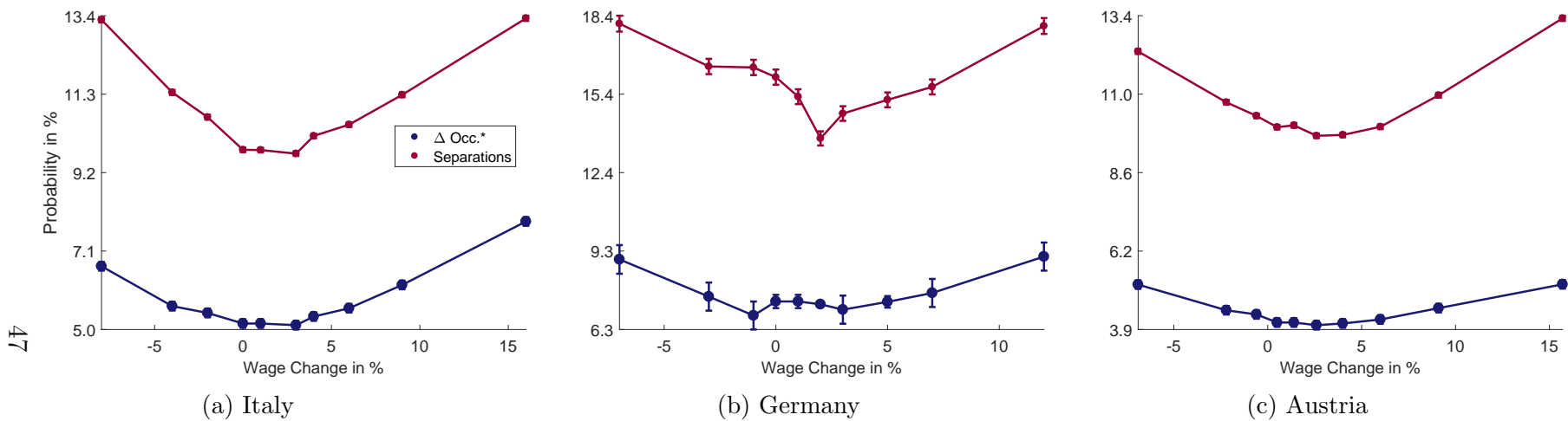
Figure 14: The U-shape relation between wage growth and job mobility

The figure shows the average separation rate and the average rate of occupational switching at time t for workers experiencing wage changes at time $t-1$ within deciles of the distribution of wage changes.
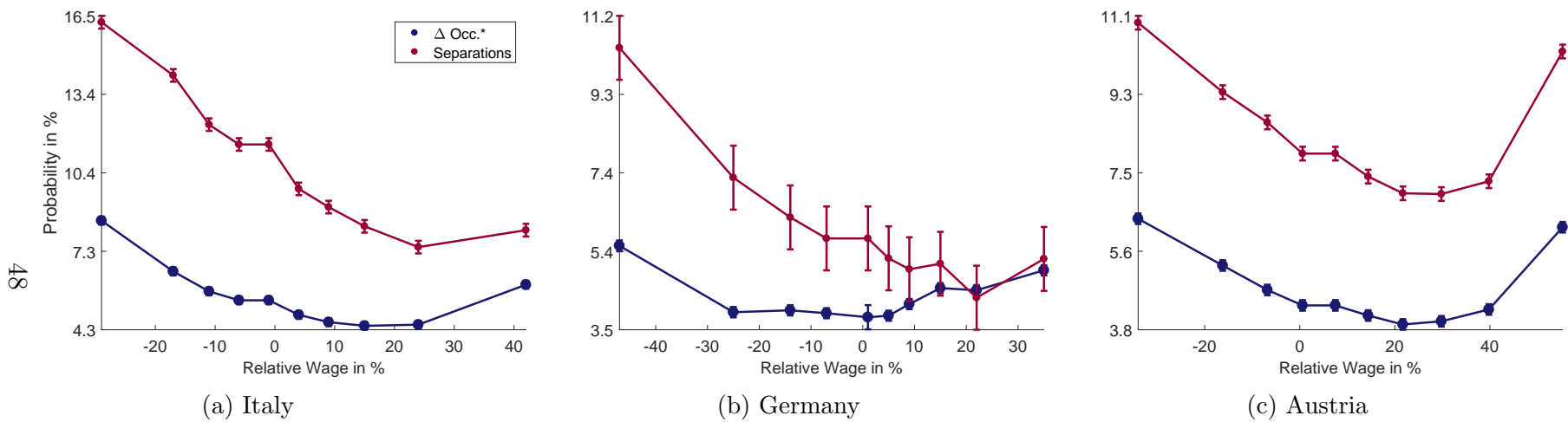
Figure 15: The relation between relative wages and job mobility

The figure shows the average separation rate and the average rate of occupational switching at time t for workers with relative wages at time $t-1$ with respect to their occupation for deciles of the distribution of wage changes.

Figure 16: The experience effect

The figure shows the average separation rate at time t for workers experiencing wage changes at time $t-1$ within deciles of the distribution of wage changes for workers with observed labor market experience above and below the mean experience level.

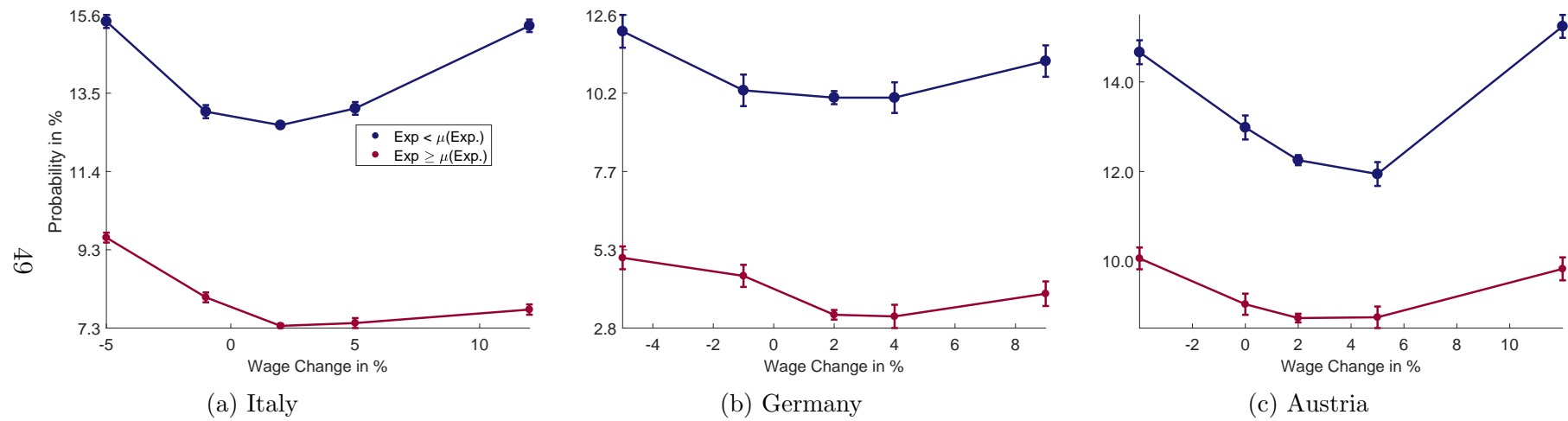|		Italy			Germany			Austria		
		(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
ΔW_{t-1}		-0.14***	-0.18***	-0.18***	-0.24***	-0.16***	-0.16***	-0.06***	-0.03	-0.08***
		(0.012)	(0.023)	(0.019)	(0.038)	(0.041)	(0.033)	(0.011)	(0.014)	(0.015)
$(\Delta W_{t-1})^2$		1.67***	1.01***	1.03***	2.72***	1.72***	1.70***	1.59***	0.53***	0.98***
		(0.071)	(0.15)	(0.13)	(0.29)	(0.34)	(0.28)	(0.060)	(0.086)	(0.075)
$\Delta W_{t-1}\times$	Exp.$_{t-1}$	-0.0020*	0.00023	0.00019	-0.0077*	-0.0020	-0.0020	- 0.005***	-0.003*	-0.004**
		(0.00089)	(0.00095)	(0.00073)	(0.0032)	(0.0031)	(0.0025)	(0.0012)	(0.0012)	(0.0012)
	F_2		0.074***	0.075***		-0.23	-0.23		-0.029*	0.01
			(0.021)	(0.016)		(0.22)	(0.16)		(0.01)	(0.013)
	F_3		-0.015	-0.014		0.26	0.26		-0.075***	-0.034*
			(0.025)	(0.02)		(0.29)	(0.30)		(0.014)	(0.014)
	F_4		-0.12***	-0.11***		0.42	0.40		-0.15***	-0.08*
			(0.028)	(0.03)		(0.44)	(0.58)		(0.016)	(0.016)
	F_5		0.022	0.03		0.24	0.23		-0.11***	-0.06***
			(0.036)	(0.04)		(0.72)	(1.10)		(0.02)	(0.02)
$(\Delta W_{t-1})^2\times$	Exp.$_{t-1}$	-0.046***	-0.018**	-0.018**	-0.14***	-0.064**	-0.063*	-0.10**	-0.04**	-0.04***
		(0.0056)	(0.005)	(0.005)	(0.026)	(0.025)	(0.022)	(0.0075)	(0.0074)	(0.0044)
	F_2		-0.22	-0.23*		0.11***	0.11***		0.23**	-0.24*
			(0.14)	(0.10)		(0.024)	(0.016)		(0.07)	(0.06)
	F_3		0.35*	0.34***		0.045	0.051		0.14	-0.091***
			(0.17)	(0.13)		(0.033)	(0.028)		(0.085)	(0.070)
	F_4		0.31***	0.29		-0.02***	-0.015***		0.20*	-0.13***
			(0.018)	(0.16)		(0.054)	(0.069)		(0.09)	(0.08)
	F_5		0.50*	0.47		0.26**	0.26**		0.55***	0.15
			(0.22)	(0.25)		(0.095)	(0.16)		(0.09)	(0.020)
Constant		0.47***	0.24***	0.24***	0.47***	0.03***	0.03***	0.41***	0.18***	0.31***
		(0.0073)	(0.0078)	(0.0066)	(0.0073)	(0.0078)	(0.007)	(0.0034)	(0.0033)	(0.002)
Observations		. 8M	.7M	.4M	.2M	.2M	.1M	1.8M	1.8M	1.8M

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, SEs in (c) obtained by Boostrap within firm bins at the spell level

Intercepts for firm types and coefficients for $\Delta N_{j,t-1}$, $N_{j,t-1}$, ten$_{i,t-1}$, $W_{i,j,t-1}$ and linear experience omitted

Table 12: Experience Effect II

	Italy		Germany		Austria	
	(a)	(b)	(a)	(b)	(a)	(b)
ΔW_{t-1}	-0.085***	-0.17***	-0.07***	-0.13***	-0.034***	-0.33***
	(0.0036)	(0.026)	(0.011)	(0.071)	(0.004)	(0.003)
$(\Delta W_{t-1})^2$	1.47***	3.47***	1.69***	1.91***	1.27***	3.15***
	(0.023)	(0.16)	(0.071)	(0.57)	(0.027)	(0.17)
$(\Delta W_{t-1})^2 \times$ Age.$_{t-1}$		-0.068***		-0.022		-0.069***
		(0.0047)		(0.0056)		(0.0051)
$(\Delta W_{t-1}) \times$ Age.$_{t-1}$		-0.0004*		-0.0009		0.0059***
		(0.0008)		(0.0032)		(0.0008)
Age.$_{t-1}$		-0.0032***		-0.0025***		-0.0029***
		(0.000058)		(0.00012)		(0.0000056)
Constant	0.66***	0.46***	0.51***	0.17***	0.49***	0.46***
	(0.0038)	(0.0072)	(0.0060)	(0.0082)	(0.0034)	(0.0036)
Observations	2.3M	.9M	.6M	.2M	1.8M	1.8M

(b) controls for $\Delta N_{j,t-1}$, $N_{j,t-1}$, ten$_{i,t-1}$, $W_{i,j,t-1}$, (a) for $W_{i,j,t-1}$.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Experience Effect III

		Italy		Germany		Austria	
		(a)	(b)	(a)	(b)	(a)	(b)
$\Delta W_{t-1} \times$	Ten $\leq \mu$(Ten), X $\leq \mu(X)$	-0.062***	-0.14***	-0.18***	-0.20***	-0.118***	-0.15***
		(0.0058)	(0.0058)	(0.013)	(0.013)	(0.0063)	(0.0063)
	Ten $\leq \mu$(Ten), X $> \mu(X)$	-0.14***	-0.13***	-0.32***	-0.27***	-0.14***	-0.10***
		(0.011)	(0.011)	(0.043)	(0.044)	(0.012)	(0.012)
	Ten $> \mu$(Ten), X $\leq \mu(X)$	-0.14***	-0.16***	-0.23***	-0.27***	-0.05***	-0.14***
		(0.0075)	(0.0075)	(0.017)	(0.017)	(0.0097)	(0.0098)
	Ten $> \mu$(Ten), X $> \mu(X)$	-0.082***	-0.061***	-0.12***	-0.17***	-0.093***	-0.078***
		(0.0064)	(0.0064)	(0.025)	(0.025)	(0.0088)	(0.0088)
$\Delta W_{t-1}^2 \times$	Ten $\leq \mu$(Ten), X $\leq \mu(X)$	2.41***	1.56***	2.83***	1.88***	1.27***	0.94***
		(0.034)	(0.034)	(0.099)	(0.100)	(0.036)	(0.036)
	Ten $\leq \mu$(Ten), X $> \mu(X)$	0.016	0.93	-3.60***	2.80***	-0.62	0.42
		(0.068)	(0.072)	(0.38)	(0.40)	(0.080)	(0.083)
	Ten $> \mu$(Ten), X $> \mu(X)$	1.62***	1.25***	2.44***	1.86***	1.35***	0.75***
		(0.049)	(0.051)	(0.13)	(0.14)	(0.058)	(0.059)
	Ten $> \mu$(Ten), X $> \mu(X)$	-0.87***	0.61***	-2.58***	2.03***	-0.61***	0.52***
		(0.043)	(0.044)	(0.22)	(0.23)	(0.060)	(0.062)
W_{t-1}		-0.073***	-0.061***	-0.070***	-0.078***	-0.070***	-0.089***
		(0.00060)	(0.00060)	(0.00073)	(0.0018)	(0.00073)	(0.0011)
Constant		0.57***	0.52***	0.47***	0.47***	0.51***	0.61***
		(0.0041)	(0.0041)	(0.0061)	(0.0061)	(0.0035)	(0.0051)
Observations		2.3M	2.3M	.6M	.6M	1.8M	1.8M

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *>** $p < 0.001$

Coefficients for Time Dummies Ommitted, (b) allows for β_0Ten× X, coefficients non-reported

Table 14: Experience Effect IV

	Italy		Germany		Austria	
	Low	High	Low	High	Low	High
1st Quintile $\Delta W_{\cdot t-1}$	0.019***	0.014***	0.0094***	0.016***	0.0033***	-0.000097
	(0.00090)	(0.00098)	(0.002)	(0.002)	(0.00076)	(0.00091)
2nd Quintile $\Delta W_{\cdot t-1}$	0.0046***	0.0043***	0.0044*	0.0099***	0.0016***	0.0040***
	(0.00079)	(0.0010)	(0.0018)	(0.0024)	(0.00066)	(0.0010)
4th Quintile $\Delta W_{\cdot t-1}$	0.0041***	0.00051	0.0033	0.0011	-0.0034***	-0.010
	(0.00080)	(0.0010)	(0.00180)	(0.0024)	(0.00069)	(0.00099)
5th Quintile $\Delta W_{\cdot t-1}$	0.014***	0.0084***	0.013***	0.0011***	0.0054***	-0.011***
	(0.00095)	(0.00097)	(0.0024)	(0.0022)	(0.00086)	(0.00092)
Constant	0.061***	0.078***	0.091***	0.102***	0.038***	0.060***
	(0.00055)	(0.00074)	(0.0013)	(0.0017)	(0.00048)	(0.00073)
Observations	.8M	.8M	.2M	.2M	.7M	.7M

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Low/High: Below/Above mean individual wage change volatility

Table 15: Above and Below Mean Wage Change Volatility Agents

6.3 Robustness Sample Selection and Wage Growth

6.3.1 Entry into Dataset

To gauge the extend of the effect of selection of work spells due to the sample begin on the U-shape effect, I consider different timings of entry into the data set. Potentially, workers that I classify as job entrants have been unemployed or otherwise outside of employment before the first observation. In that sense I could systematically select workers with potentially more variable employment relationships. To test this, I consider workers that have started one year after the first year of observation in the dataset. This timing is supported by the fact that 50% of workers in the Italian (Austrian) baseline sample who separate and will be observed in a subsequent work spell have less than or equal to 6 (11) months of unemployment until the next spell.

Table **??** shows that the U-shape effect is robust to this shifted entry where column (b) reports results for the sample with a delayed entry.

	Italy		Germany		Austria	
	(a)	(b)	(a)	(b)	(a)	(b)
ΔW_{t-1}	-0.085***	-0.12***	-0.07***	-0.07***	-0.034***	0.020***
	(0.0036)	(0.0058)	(0.0094)	(0.0091)	(0.0043)	(0.0056)
$(\Delta W_{t-1})^2$	1.47***	1.90***	1.68***	1.50***	1.12***	0.95***
	(0.026)	(0.036)	(0.067)	(0.075)	(0.027)	(0.033)
W_{t-1}	-0.084***	-0.11***	-0.075***	-0.073***	-0.067***	-0.12***
	(0.00058)	(0.00091)	(0.0013)	(0.0012)	(0.00075)	(0.0009)
Constant	0.75***	0.87***	0.51***	0.49***	0.49***	0.59***
	(0.0043)	(0.0060)	(0.0060)	(0.0060)	(0.0034)	(0.0041)
Observations	2M	1.1M	.6M	.6M	1.8M	.9M

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: The Effect of delayed Entry on the U-shape

6.3.2 Apprentices

Apprentices have been excluded from the dataset to reduce variations in actual hours worked across workers. Apart from variations in hours, apprenticeship contracts often include various non-wage payments as for instance tuition for vocational training schools or payments for travel. Also from the firm side, the cost of an employeee differs for apprentices: In Italy, for instance, firms benefit from tax relief in the form of exemption from employer welfare and social security contributions for the length of the contract.[20] Finally, apprenticeship

---

[20]cf. Samek et al. (2013)

contracts have fixed durations unless broken before term. Hence we expect that the U-shape effect is weaker under the addition of apprentices. This is the case as seen in table **??** where column (b) includes apprentices.

	Italy		Germany		Austria	
	(a)	(b)	(a)	(b)	(a)	(b)
ΔW_{t-1}	-0.085***	-0.050***	-0.07***	0.14***	-0.07***	-0.06***
	(0.0036)	(0.0023)	(0.0094)	(0.0091)	(0.0043)	(0.0041)
$(\Delta W_{t-1})^2$	1.47***	0.82***	1.68***	1.24***	1.12***	1.50***
	(0.026)	(0.014)	(0.075)	(0.052)	(0.027)	(0.030)
W_{t-1}	-0.084***	-0.049***	-0.076***	-0.18***	-0.067***	-0.076***
	(0.00058)	(0.00038)	(0.0013)	(0.00072)	(0.00075)	(0.00041)
Constant	0.75***	0.41***	0.51***	1.00***	0.49***	0.41***
	(0.0043)	(0.0025)	(0.0060)	(0.0033)	(0.0034)	(0.0025)
Observations	2M	3.8M	.6M	.7M	2M	3.5M

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Including Apprentices

6.3.3 Wage Growth

As discussed in Guvenen et al. (2016) and Davis et al. (1998), log wage change measures can be problematic if computed based on very low wage observations. These concerns are mostly addressed by focusing on the 98% of the support of wage changes in the sample. To fully address concerns about the measurement of wage changes, I estimate the baseline specification also with the arc percentage as proposed in Davis et al. (1998), that is

$$\Delta W_{t-1} = \frac{W_{t-1} - W_{t-2}}{(W_{t-1} + W_{t-2})/2}$$

Table 18, column (2) shows that results are similar for both measures of wage changes.

53

	Italy		Germany		Austria	
	(a)	(b)	(a)	(b)	(a)	(b)
ΔW_{t-1}	-0.085***		-0.07***		-0.034***	
	(0.0036)		(0.0094)		(0.0043)	
$(\Delta W_{t-1})^2$	1.47***		1.68***		1.12***	
	(0.023)		(0.075)		(0.026)	
W_{t-1}	-0.084***	-0.084***	-0.076***	-0.067***	-0.086***	-0.086***
	(0.00058)	(0.00058)	(0.0013)	(0.0012)	(0.00075)	(0.00075)
$\Delta W_{t-1}^{\mathrm{arc}}$		-0.086***		-0.086***		-0.023***
		(0.0036)		(0.0096)		(0.0043)
$(\Delta W_{t-1}^{\mathrm{arc}})^2$		1.49***		1.84***		0.87***
		(0.023)		(0.023)		(0.023)
Constant	0.66***	0.66***	0.51***	0.46***	0.49***	0.49***
	(0.0038)	(0.0038)	(0.0059)	(0.0053)	(0.0034)	(0.0034)
Observations	2.3M	2.3M	.6M	.6M	1.8M	1.8M

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Different Wage Growth Measures

6.3.4 Trimming and Wage Concept in Italian Data

As noted in Galizzi and Lang (1998) the detection of cases of temporary absence from work, insured through the CIG, could create measurement error for the case of Italy. As agents with temporary absence from work could have been registered on payroll despite not having contributed to the labor force, their registered wage payments would be biased. Under this system, workers are payed 80% of their previous income. As a robustness exercise, I follow Galizzi and Lang (1998) and cap wage changes at 25 and -20 %. The following table shows that the main specification is not qualitatively altered when implementing this restriction (cf. column (2) of table 20).

	(1)	(2)
$\Delta W_{i,j,t-1}$	-0.11***	-0.11***
	(0.0036)	(0.0036)
$(\Delta W_{i,j,t-1})^2$	1.41***	1.64***
	(0.023)	(0.027)
Constant	0.11***	0.11***
	(0.00023)	(0.00024)
Observations	2.33M	2.31M

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ ¿

Table 19: Implementing Caps to Wage Change Distribution

The Italian dataset further allows to compute wages at different frequencies. I find no qualitative differences when using monthly, weekly or daily wage concepts. In table 20 I also control for the average wage at the firm $\mu(W_{t-1})^J$ following Galizzi and Lang (1998).

	Month (a)	Month (b)	Month (c)	Week (a)	Week (b)	Week (c)	Day (a)	Day (b)	Day (c)
ΔW_{t-1}	-0.084***	-0.18***	-0.11***	-0.091***	-0.19***	-0.14***	-0.11***	-0.19***	-0.14***
$\mu(W_{t-1})^J$	0.0025	0.0022		-0.0060	-0.0091		0.014***	0.011***	
ΔW_{t-1}^2		1.13***	1.68***		1.17***	1.84***		1.04***	1.66***
Observations	.8M	.8M	2M	.8M	.8M	2M	.5M	.5M	1.2M

All specifications include controls for age, firm size, sector and qualification.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 20: Different Wage Concepts

6.3.5 Censoring

Right censoring of the wage information in the Austrian and German[21] data set could potentially bias my results by affecting my measure of wage changes. To study the potential effect of different censoring thresholds on the estimate of the baseline specification, I follow Borovickova and Shimer (2017) and vary the annual wage cap incrementally. Specifically, I reduce the censoring threshold step-wise up to a sampe size of 50 % of the true sample. I then re-estimate the subsequent linear probability model on the synthetic sample

$$\text{Separation}_{i,j,t} = \alpha + \beta_0 \Delta W_{i,j,t-1} + \beta_1 \Delta W_{i,j,t-1}^2 + \epsilon_{i,j,t}$$

Figure 17b and 17a show the change in the coefficients as the share of censored observations increases from 0 to 50% for Austria (left panel) and Germany (right panel). In the German setting there are two distinct censoring thresholds whose respective salience is not inferable from the data. To allow that workers hit the threshold only part through the year (and following Dustmann et al. (2009)), I consider an observation as censored if it is three euros below the censoring limit. Experimenting with changes to this limit did not alter the results significantly. For this exercise, I first report results for the sample with censoring detected through this procedure (first observation for Germany). For comparison with the results for Austria, I then consider the lower of the two thresholds to be always binding, which leads to a censoring rate of 20%.

In all cases the U-shape effect is evident. Strikingly, the linear effect of wage growth on separations as well as the average separation rate vary only slightly as the censoring threshold

---

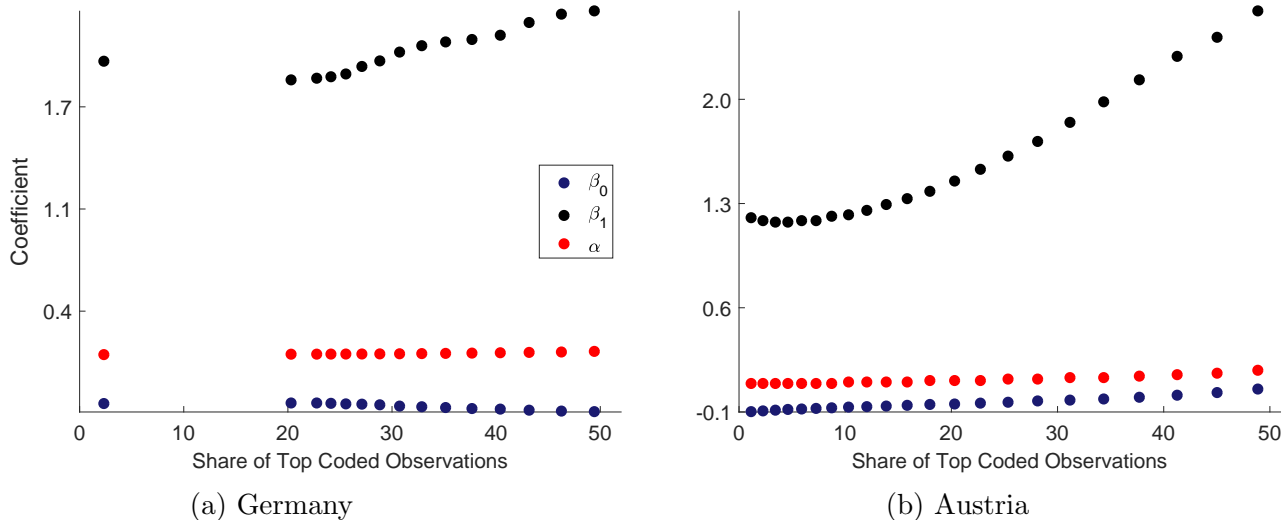[21]Censoring is absent in the Italian data set.

Figure 17: Effect of Censoring

The figure shows the coefficients of the linear probability model when varying the sample size by lowering a pseudo censoring limit.

increases, yet the quadratic term varies with the threshold. The variation of the quadratic coefficient with the censoring threshold supports a view in which the non-linear effect of wage growth varies for different populations and is notably stronger for low wage matches.

6.4 Movements

To understand the reason of mobility on the U-shape, I consider the direction of moves for workers in my sample. To do that, I compute the level of average firm wages $\hat{\mu}_j$ for out-of-sample workers with valid wage observations. These workers had above 30 years of age at entry into my dataset and were hence discarded from the main analysis. Moreover, I compute the variance of wage changes within firms for this group of workers $\hat{\sigma}_j$.[22] Firm averages and volatilities computed for less than ten workers were excluded from the analysis.

$$\hat{\sigma}_j = \left(\frac{1}{N-1} \sum^N \left(W_{i,j,t} - \mu(W_{i,j,t}) \right) \right)^{(1/2)} \qquad \hat{\mu}_j = \frac{1}{N} \sum^N W_{i,j,t}$$

I then compute the percentage change in these two measures for workers moving between firms within quintiles of the wage change distribution. Results are reported in table 21. I find that especially for Italy, on average workers move to firms with higher average wages, and this is also true for those at the left support of wage changes. Moreover, workers move to

---

[22]In my theoretical model without surplus renegotiation but dynamic match quality, $\hat{\sigma}_j$ proxies for the true firm specific volatility of shocks.

firms with higher volatility of wage changes. This latter fact could mirror either the within-firm correlation of productivity and volatility or the increasing occurrence of on-the-job wage growth through wage renegotiation at better firms. Note further that I do find some evidence of movements to lower quality firms for Austria. These results are not reported for Germany

	Italy		Austria	
	$\Delta\hat{\sigma}_j$	$\Delta\hat{\mu}_j$	$\Delta\hat{\sigma}_j$	$\Delta\hat{\mu}_j$
1st Quintile ΔW_{t-1}	-0.088***	-0.019***	-0.068***	-0.015***
	(0.012)	(0.0030)	(0.010)	(0.0022)
2nd Quintile ΔW_{t-1}	-0.023	-0.0069	0.010	-0.017***
	(0.012)	(0.0031)	(0.011)	(0.0023)
4th Quintile ΔW_{t-1}	-0.017	-0.00064	-0.039	-0.011***
	(0.012)	(0.0031)	(0.011)	(0.0023)
5th Quintile ΔW_{t-1}	-0.078**	0.0032	-0.049**	0.0038
	(0.012)	(0.0029)	(0.010)	(0.0022)
Cons.	0.17***	0.056***	0.23***	0.014***
	(0.009)	(0.0022)	(0.008)	(0.0017)
Observations	60K	60K	130K	160K

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Entries are in percentage differences from sending firm

Table 21: Changes in Firm Characteristics for Movers

due to too low case counts. This analysis requires that a worker is observed twice at firms in which all coworkers are observable. This is a highly unlikely case in the German data due to its sampling design.

6.5 Surplus Function

In the following, I report the surplus functions for the model with renegotiation of the surplus share. Let $W(J, I, O, M)$ denote the value of an employed worker I at firm J with outside option O at match M. Moreover, denote by $U(I)$ and $P(J, I, O, M)$ the value of an unemployed worker and the value of a job, respectively. Further, denote by $S(J, I, O, M) = S(J, I, M)$ the joint surplus of the match. Due to the invariance of total surplus to the sharing agreement, the surplus function is independent of the outside option.

In this environment, there is the following set of mobility situations. If workers match with a firm out of unemployment, their outside option is zero and they enter the match if the surplus at the firm exceeds zero. The worker then receives $W(J, I, 0, M^0) - U(I) = \alpha S(J, I, M^0)$. If workers match with a firm J' during on-the-job-search, they can leave their current firm J to receive $W(J', I, J, M^0) - U(I) = S(J, I, M^0) + \alpha(S(J', I, M^0) - S(J, I, M^0))$ at the new firm. The worker will move to J' if the total surplus at the new firm exceeds the

surplus at his current firm. I denote the set of firms J' for which the worker will move as $\mathcal{M}_1 : \{S(J', I, M^0) > S(J, I, M)\}$. If moving to the new firm is not profitable, then workers with previous outside option O can still renegotiate their current surplus share to obtain: $W(J, I, J', M) - U(I) = S(J', I, M^0) + \alpha(S(J, I, M) - S(J', I, M^0))$. This strategy is optimal if the surplus at the previous outside option is lower than the surplus at the new firm, hence for the set of firms $\mathcal{M}_3 : \{S(O, I, M^0) < S(J', I, M^0) < S(J, I, M)\}$. Finally, in the presence of learning, it is possible that the believe about the quality of the match changes such that the worker's or firm's incentive constraints are violated. In this case, I assume that workers and firms renegotiate their contract to satisfy the incentive compatibility constraints $0 < W(J, I, O, M) - U(I) < S(J, I, M)$. I assume that the worker gets all the surplus $(W(J, I, O, M) - U(I) = S(J, I, M))$ whenever his incentive constraint is violated (if $W(J, I, O, M) - U(I) > S(J, I, M)$) and reversely for the firm $W(J, I, O, M) - U(I) = 0$ if $W(J, I, O, M) - U(I) < 0$. In summary, there are two cases for separations in this model: once by switching employers after on-the-job search or upon belief changes that push match surplus below zero.

The value of the match to the worker with outside option $O = \{\mu_o, \sigma_o^2\}$ is composed as before of the continuation value of staying with the firm or moving upon receiving an outside offer. Similarly, the worker receives the unemployment value $U(I')$ if updating leads to endogenous separations. In addition, when receiving an outside offer that leads to surplus renegotiation ($\mathcal{M}_3$), the worker can change the outside option.

$$
\begin{aligned}
W(J, I, O, M) \;=\; \max\Bigg\{ & 0, w + \beta\delta U(I) + \beta(1-\delta)\bigg[\lambda_1\bigg(\int_{\mathcal{M}_2}\int_{\mathcal{M}_1} W(J', I', J, M^0)dF(J')dG^J(I') \\
& + \int_{\mathcal{M}_2}\int_{\mathcal{M}_3} W(J, I', J', M')dF(J')dG^J(I')\bigg) + \int_{\mathcal{M}_2}\bigg(1 - \lambda_1\int_{\mathcal{M}_1,\mathcal{M}_3} dF(J')\bigg) \\
& \min\{W(J, I', O, M'), S(J, I', M') + U(I')\}dG^J(I') \\
& + \int\bigg(1 - \int_{\mathcal{M}_2} dG^J(I')\bigg) U(I')dG^J(I')\bigg]\Bigg\}
\end{aligned}
$$

The value of being unemployed is unchanged. The surplus of the match to the worker is then described as

$$
\begin{aligned}
W(\cdot) - U(I) \;=\; & \max\Bigg\{ 0, w - z - \beta\lambda^0\alpha \int_{\mathcal{M}_1} S(J', I, M^0)dF(J') + \beta(1-\delta)\bigg(\int U(I') - U(I)dG^J(I') \\
& + \lambda_1 \bigg(\int_{\mathcal{M}_2} \int_{\mathcal{M}_1} W(J', I', J, M^0) - U(I')dF(J')dG^J(I') \\
& + \int_{\mathcal{M}_2} \int_{\mathcal{M}_3} W(J, I', J', M') - U(I')dF(J')dG^J(I') \\
& + \int_{\mathcal{M}_2} \Big(1 - \lambda_1 \int_{\mathcal{M}_1,\mathcal{M}_3} dF(J') \Big) S_S dG^J(I') \bigg) \bigg) \Bigg\}
\end{aligned}
$$

where $S_S = \max\{0, \min\{W(J, I', O, M') - U(I'), S(J, I', M')\}\}$. The value to the firm is

$$
\begin{aligned}
P(J, I, O, M) \;=\; & \max\Bigg\{ 0, E[y_{i,j,t}] - w + \beta(1-\delta)\bigg[\lambda_1 \int_{\mathcal{M}_2} \int_{\mathcal{M}_3} P(J, I', J', M')dF(J')dG^J(I') \\
& + \int_{\mathcal{M}_2} \Big(1 - \lambda_1 \int_{\mathcal{M}_1,\mathcal{M}_3} dF(J') \Big) P(J, I', O, M')dG^J(I') \bigg] \Bigg\}
\end{aligned}
$$

Using the contract rule, that is $W(J, I, O, M) - U(I) = S(O, I, M^0) + \alpha(S(J, I, M) - S(O, I, M^0))$ the joint surplus is hence

$$
\begin{aligned}
S(J, I, M) \;=\; & \max\Bigg\{ 0, E[y_{i,j,t}] - z + \beta(1-\delta)\bigg[\int U(I') - U(I)dG^J(I') + \int_{\mathcal{M}_2} S(J, I', M')dG^J(I') \\
& + \lambda_1 \int_{\mathcal{M}_2} \int_{\mathcal{M}_1} \alpha(S(J', I', M^0) - S(J, I', M^0)) + (S(J, I', M^0) - S(J, I', M'))dG^J(I')dF(J') \bigg] \\
& - \beta\alpha\lambda_0 \int_{\mathcal{M}_{1(u)}} S(J', I, M^0)dF(J') \Bigg\}
\end{aligned}
$$

Using the contract rule, together with the equation for the surplus of the match to the worker, we obtain for wages

$$
\begin{aligned}
w(J, I, O, M) \;=\;& SS(J, I, O, M) + z - \beta(1-\delta)\left(\int U(I') - U(I)dG^J(I')\right. \\
+\;& \lambda^1\left(\int_{\mathcal{M}_2}\int_{\mathcal{M}_1} SS(J', I', J, M^0)dF(J')dG^J(I')\right. \\
+\;& \int_{\mathcal{M}_2}\int_{\mathcal{M}_3} SS(J, I, J', M')dF(J')dG^J(I')\Big) \\
+\;& \int_{\mathcal{M}_2}\left(1 - \int_{\mathcal{M}_1\cup\mathcal{M}_3} dF(J')\right)\max\{0, \min\{SS(J, I', O, M'), S(J, I', M')\}\}dG^J(I')\Big) \\
+\;& \beta\lambda^0\alpha\int_{\mathcal{M}_1} S(J', I, M^0)dF(J')
\end{aligned}
$$

where
$$
\begin{aligned}
&\mathcal{M}_1 : \{S(J', I', M^0) > S(J, I', M')\} \\
&\mathcal{M}_2 : \{S(J, I', M') > 0\} \\
&\mathcal{M}_3 : \{S(O, I', M^0) < S(J', I', M^0) < S(J, I', M')\} \\
&SS(J, I, O, M) = S(O, I, M^0) + \alpha(S(J, I, M) - S(O, I, M^0))
\end{aligned}
$$

6.6 Learning Process

The output equation and the law of motion for the productivity can be interpreted as observation and state equation in a filtering problem.

$$
\begin{aligned}
y_{i,j,t} \;&=\; v(\mu_0, \mu_j, a_i) + n_{i,j,t} \\
n_{i,j,t} \;&=\; \rho n_{i,j,t-1} + \eta_{i,j,t}
\end{aligned}
$$

Let $\beta_{i,t|t} = [N_{ijt} \quad A_{i,t}]'$ be the time t vector of beliefs about match specific productivity $n_{i,j,t}$ and worker's intrinsic productivity a_i, summarized in vector $\widetilde{\beta}_{i,j,t} = [n_{i,j,t} \quad a_i]'$. Further denote by $\Omega_{i,t|t}$ the covariance matrix of beliefs after observing information up to date t. Using the Kalman filter, the beliefs then follow (omitting the worker and firm index)

$$
\begin{aligned}
\Omega_{t|t-1} \;&=\; \Psi\Omega_{t-1|t-1}\Psi' + \Phi \\
\beta_{t|t} \;&=\; \Psi\beta_{t-1|t-1} + (\Omega_{t|t-1}X')S_{yy}^{-1}(y_t - \beta_{t|t-1}X) \\
\Omega_{t|t} \;&=\; \Omega_{t|t-1} - (\Omega_{t|t-1}X')S_{yy}^{-1}(X\Omega_{t|t-1})
\end{aligned}
$$

where $X = [1 \quad \mu_j]$ $\qquad S_{yy} = J_h \Omega_{t|t-1} J_h'$

$\qquad \Psi = \text{diag}([\rho \quad 1]) \quad \Phi = \text{diag}([\sigma_j^2 \quad 0])$

$\qquad \beta_t = [N_\tau \quad A_t]' \qquad E[\widetilde{\beta}_{t-1}] \sim N(\beta_{t-1}, \Omega_{t-1})$

Given the initial belief $\beta_t \sim N([0 \quad A_t], \text{diag}[0 \sigma_{a,t}])$ and extending the updating expressions,

we arrive at the recursive equation in the text. Hence, in this setting, learning has a simple recursive structure such that the covariance matrix of beliefs $\Omega_{t|t}$ at time t after observing output at time t is a function of the variance of beliefs about the worker's quality (and an indicator variable about a new match I_{OTJ}). Hence, only the state vector of the individual and the firm characteristics are required to compute the covariance matrix of beliefs about dynamic match productivity. All together, the learning process follows

$$
\begin{aligned}
\Omega_{t|t} &= \sigma_{a,t}^2 \Omega \\[4pt]
\sigma_{a,t}^2 &= \frac{\sigma_{a,t-1}^2}{1+s} \\[4pt]
\beta_{t|t} &= \Psi \beta_{t-1|t-1} + \frac{1}{(1+s)(1-I_{OTJ}\rho)} \begin{bmatrix} 1 - I_{OTJ}\rho(1+s) \\ s \end{bmatrix} \xi_t
\end{aligned}
$$

where $\quad \Psi = \text{diag}([\rho \quad 1]) \quad s = \sigma_{a,t-1}^2 (1 - I_{OTJ}\rho)^2 / \sigma_j^2$

$\qquad \Omega = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \qquad \xi_t = y_t - v(\mu_j, A_t) - \rho N_{i,j,t}$

6.7 Variance of Changes in Beliefs

In the following I derive the formula for the variance of changes in beliefs $A_{i,t}$. I omit the index i for convenience. First, note that

$$
\Delta A_t = \beta_{t-1} \left[a - A_{t-1} + \epsilon_{i,t} \right]
$$

where $\beta_{t-1} = \frac{s_{t-1}}{1+s_{t-1}}$. By recursive replacement in

$$
A_{t-1} = A_{t-2}(1 - \beta_{t-2}) + \beta_{t-2} a_i + \beta_{t-2} \epsilon_{t-1}
$$

we can obtain that

$$
A_t = \beta_{t-1} \left(\frac{A_0}{(\sigma_j^2)^{t-1}} \frac{1}{s_0} + a_i \left(\sum_{i=0}^{t-1} \left(\frac{1}{\sigma_j^2} \right)^i \right) + \left(\sum_{i=0}^{t-1} \epsilon_{t-i} \left(\frac{1}{\sigma_j^2} \right)^i \right) \right)
$$

Note that β_{t-1} is a function of t, the experience of the worker only. Hence we obtain the formula for the variance of changes in A_t as

$$\text{Var}\left(\Delta A_t\right) = \beta_{t-1}^2 \left(\frac{\beta_{t-2}^2}{(\sigma_j^4)^{t-2}} \frac{\text{Var}(A_0)}{s_0^2} + \text{Var}(a_i)\left(1 + \beta_{t-2}^2 \sum_{i=0}^{t-2} \left(\frac{1}{\sigma_j^4}\right)^i \right) + \sigma_j^2 \left(1 + \beta_{t-2}^2 \sum_{i=0}^{t-2} \left(\frac{1}{\sigma_j^4}\right)^i \right) \right)$$

where $\beta_{t-2} = \beta_{t-1}(1 + s_{t-1})/\sigma_j^2$. The variance of ΔA_t is therefore increasing in β_{t-1} which is itself decreasing in experience.

6.8 Dynamic Match Productivity and Wages

In the following, assume that the worker reaps the whole surplus of the match. In this case, wages equal expected output such that

$$
\begin{aligned}
\Delta W_t &= \Delta A_t + \Delta N_t \\
&= (\rho - 1)N_{t-1} + \xi_t \\
&= (a_i - A_{t-1}) + (n_t - N_{t-1})
\end{aligned}
$$

Moreover, note that

$$N_t = -A_t + (a_i + n_t)$$

such that in fact $\Delta W_t = n_t - n_{t-1} = \Delta n_t$.

6.9 Legal Settings

In general, all three datasets are well suited for the analysis due to their size and their origin in administrative records, compressing the scope for measurement errors. However, the datasets differ with respect to their institutional environment.

In Germany, a culture of decentralized wage bargaining at the region-industry or firm level, coupled with a decline in the importance of centralized bargaining since the early to mid 1990s (cf. among others Dustmann et al. (2014), Addison et al. (2015)), creates a relatively flexible wage bargaining environment. In fact, since 1995 to 2008, Germany observed a reduction in coverage by industry-wide agreements from 75 to 56 % and a fall of coverage by firm-level agreements from 10.5 to 9% Dustmann et al. (2014). At the same time Germany wittiness an increasing inequality of wages within the covered sector. Differently from Italy, the German bargaining structure is apolitical and builds on contracts and mutual

agreements within unions and firm specific work councils. Firms have discretionary power to decide weather to accept union contracts or to negotiate deviations from agreements with the works council, irrespective of the union membership of their workers. As in Italy, firing regulations are traditionally important. However, after a series of law changes, firms below 10 employees are largely excluded from restrictive firing regulations since 2004 (cf. Guetzgen (2007)).

In Italy, collective bargaining occurs at several at times overlapping levels. Traditionally, national agreements set the frame and regional agreements set policies according to the agreed guidelines. Since the 1980's, the importance of national agreements declined in favor of regional, company or plant-level agreements.In fact, in 1990, 38% of firms reported using company or plant-level agreements (Katz (1993)). When in place, collective agreements at the national level are all-encompassing within a sector and independent of union meme-bership of workers or the allegiance of the firm, such that de facto all Italian workers are covered by collective agreements (Dell'Aringa and Lucifora (1994)). Regional or local agree-ments are subordinate to higher ranked negotiations, and can only be accumulative on top of nationally agreed wage levels. At the last stage, firms can set productivity related wage premia. In addition to these wage setting rules, Italy experienced a history of regulations concerning layoffs, stipulating rules for severance payments and "unjust dissmisal" as well as collective dissmissals. Yet, until 1990, rules for "unjust dissmissal" or collective dissmissals only concerned firms above 15 employees. All firms in Italy have been subject to severance payments upon separation of workers.These severance payments were accumulated in form of a savings account of annual wage payments at the firm level. These accounts were often used as a form of liquidity provision to Italian firms (cf. Calcagno et al. (2011)). In addition, managers ("dirigenti") were always excluded from labor protection measures and could be fired at any moment without possibility for legal recourse.

Through a highly centralized bargaining framework, that combines employers, employee rep-resentatives, unions and government officials, the Austrian labor market is comparable to the Italian system. Collective agreements set minimum wages at the industry and regional level which can be adjusted at the firm level in a similar fashion as in Italy. Despite the institutional framework, turnover rates in Austria are comparable to the US (cf. Stiglbauer et al. (2003)), giving witness of a relatively flexible labor market despite regulations.

6.10 Learning of or Learning about

An elevated variance of wage changes for young workers could not only reflect learning about skills but could also signal an uneven skill accumulation at the start of a worker's career. For instance, in the learning framework of Jovanovic and Nyarko (1995) agents learn at a

decreasing rate by observing random learning signals.

To distinguishing between learning about skills and uneven human capital accumulation to drive the early career wage change variance, I follow Nagypál (2007). She points to the insulating effect of human capital accumulation and studies differences in the experience profile of endogenous separations in both learning models. In the Jovanovic and Nyarko (1995) model of learning on the job, inexperienced workers learn at a higher but decreasing speed and have a lower stock of human capital. As a result, these workers are more likely to experience endogenous separations and feature a high variance of wage changes. On the other hand, in the model of learning about the type of the worker (as seen in this paper), volatile wage changes do not increase the subsequent separation propensity.

In the following, I depart from this test in two ways. First, to allow for differences in learning speed across firms, I do not focus on the experience profile but rather consider wage changes as an indicator of the volatility of learning signals. Moreover, I do not study endogenous separations but rather focus on the duration of non-employment after an observed separation. In this way, I avoid the complications linked to the identification of endogenous separations while still being able to use the effect of differences in the human capital stock for identification. I assume that workers with higher human capital stocks have a lower likelihood of layoff and have lower non-employment durations upon separation.

Hence, I consider the mean duration of non-employment after a separation as a function of the last observed wage change in the previous job. As before, I use quintiles of the wage change distribution for this exercise.

If indeed agents with volatile wage changes have lower human capital stocks, one would expect longer periods of non-employment for agents at the extremes of the wage change support. In table 22 I show that there is only a weak difference in the duration of observed non-employment for agents that had high or low wage changes during the previous work spell for Italy. Moreover, the effect disappears once controlling for experience. In Austria, however, I do find evidence for this effect to play a role even after controlling for experience. This could reflect differences in the pervasiveness of apprenticeship schemes which reduce information frictions at the start of employment relationships.

	Italy		Germany	Austria	
1st Quintile	0.36*	0.55***		0.80***	0.78***
	(0.17)	(0.17)		(0.09)	(0.09)
2nd Quintile	0.029	0.36*		0.27**	0.27**
	(0.17)	(0.17)		(0.09)	(0.09)
4th Quintile	0.74***	0.035		-0.01	-0.10
	(0.17)	(0.17)		(0.09)	(0.10)
5th Quintile	1.93***	0.015		0.82***	0.36***
	(0.17)	(0.17)		(0.09)	(0.09)
Exp.$_{t-1}$		-0.63***			-0.27***
		(0.0085)			(0.0083)
Constant	7.01***	13.6***		5.12***	7.14***
	(0.12)	(0.15)		(0.07)	(0.09)
Observations	200K	200K		180K	180K

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

RESULTS FOR GERMANY COMING SOON (CONFIDENTIALITY CLEARING).

Table 22: Duration Non-Employment After Separation

References

Addison, John T. et al. (2008). "The Demand for Labor: An Analysis Using Matched Employer–Employee Data from the German LIAB. Will the High Unskilled Worker Own-Wage Elasticity Please Stand Up?" *Journal of Labor Research* 29.2, 114–137.

Addison, John T. et al. (2015). "Declining Unions and the Coverage Wage Gap: Can German Unions Still Cut It?" *Journal of Labor Research* 36.3, 301–317.

Allison, Paul D. (1999). "Comparing Logit and Probit Coefficients Across Groups". *Sociological Methods & Research* 28.2, 186–208.

Altonji, Joseph G., Anthony A. Smith, and Ivan Vidangos (2013). "Modeling Earnings Dynamics". *Econometrica* 81.4, 1395–1454.

Anger, Silke (2011). "The cyclicality of effective wages within employer–employee matches in a rigid labor market". *Labour Economics* 18.6, 786 –797.

Bartel, Ann P. and George J. Borjas (1978). *Wage Growth and Job Turnover: An Empirical Analysis*. Working Paper 285. National Bureau of Economic Research.

Bartolucci, Cristian, Francesco Devicienti, and Ignacio Monzón (2015). *Identifying Sorting in Practice*. IZA Discussion Papers 9411. Institute for the Study of Labor (IZA).

Bingley, Paul and Niels Westergaard Nielsen (2006). "Job Changes and Wage Growth over the Careers of Private Sector Workers in Denmark". *Structural Models of Wage and Employment Dynamics*, 309–330.

Borovickova, Katarina (2013). "What Drives Labor Market Flows?" mimeo.

Borovickova, Katarina and Robert Shimer (2017). "High Wage Workers Work for High Wage Firms". mimeo.

Brown, James N. (1989). "Why Do Wages Increase with Tenure? On-the-Job Training and Life-Cycle Wage Growth Observed within Firms". *The American Economic Review* 79.5, 971–991.

Calcagno, Riccardo, Roman Kraeussl, and Chiara Monticone (2011). "An analysis of the effects of the severance payment reform on credit to Italian SMEs". *Journal of Financial Economic Policy* 3.3, 243–261.

Card, David (2001). "The Effect of Unions on Wage Inequality in the U.S. Labor Market". *ILR Review* 54.2, 296–315.

Card, David, Thomas Lemieux, and W. Craig Riddell (2003). "Unionization and Wage Inequality: A Comparative Study of the U.S, the U.K., and Canada".

Card, David, Jörg Heining, and Patrick Kline (2013). "Workplace Heterogeneity and the Rise of West German Wage Inequality". *The Quarterly Journal of Economics*.

Christensen, Bent Jesper et al. (2005). "On-the-Job Search and the Wage Distribution". *Journal of Labor Economics* 23.1, 31–58.

Davis, S.J., J.C. Haltiwanger, and S. Schuh (1998). *Job Creation and Destruction*. MIT Press.

Davis, Steven J. and Till M. von Wachter (2011). *Recessions and the Cost of Job Loss*. Working Paper 17638. National Bureau of Economic Research.

Dell'Aringa, Carlo and Claudio Lucifora (1994). "Collective bargaining and relative earnings in Italy". *European Journal of Political Economy* 10.4, 727 –747.

DiNardo, John, Nicole M Fortin, and Thomas Lemieux (1996). "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach". *Econometrica* 64.5, 1001–1044.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg (2009). "Revisiting the German Wage Structure". *The Quarterly Journal of Economics* 124.2, 843–881.

Dustmann, Christian et al. (2014). "From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy". *Journal of Economic Perspectives* 28.1, 167–88.

Eeckhout, Jan and Xi Weng (2009). *Assortative Learning*. Tech. rep. working paper.

Farber, Henry S. (1994). "The Analysis of Interfirm Worker Mobility". *Journal of Labor Economics* 12.4, 554–593.

Fischer, Gabriele et al. (2008). "The IAB establishment panel: from sample to survey to projection". 200801.

Fuchs-Schündeln, Nicola, Dirk Krueger, and Mathias Sommer (2010). "Inequality trends for Germany in the last two decades: A tale of two countries". *Review of Economic Dynamics* 13.1, 103 –132.

Galizzi, Monica and Kevin Lang (1998). "Relative Wages, Wage Growth, and Quit Behavior". *Journal of Labor Economics* 16.2, 367–390.

George Baker Michael Gibbs, Bengt Holmstrom (1994). "The Wage Policy of a Firm". *The Quarterly Journal of Economics* 109.4, 921–955.

Gibbons, Robert and Michael Waldman (1999). "A Theory of Wage and Promotion Dynamics Inside Firms". *The Quarterly Journal of Economics* 114.4, 1321–1358.

Gielen, Anne C. and Jan C. van Ours (2006). *Why Do Worker-Firm Matches Dissolve?* IZA Discussion Papers 2165. Institute for the Study of Labor (IZA).

Grinza, Elena (2014). "Excess Worker Turnover and Firm Productivity". mimeo.

Groes, Fane, Philipp Kircher, and Iourii Manovskii (2015). "The U-Shapes of Occupational Mobility". *The Review of Economic Studies* 82.2, 659–692.

Guetzgen, Nicole (2007). "Job and Worker Reallocation in German Establishments: The Role of Employers' Wage Policies and Labour Market Institutions". mimeo.

Guvenen, Fatih and Anthony A. Smith (2014). "Inferring Labor Income Risk and Partial Insurance From Economic Choices". *Econometrica* 82.6.

Guvenen, Fatih et al. (2016). "What Do Data on Millions of U.S. Workers Say About Life Cycle Income Risk?"

Hagedorn, Marcus and Iourii Manovskii (2013). "Job Selection and Wages over the Business Cycle". *American Economic Review* 103.2, 771–803.

Haltiwanger, John et al. (2017). *Cyclical Job Ladders by Firm Size and Firm Wage*. Working Paper 23485. National Bureau of Economic Research.

Hirsch, Boris and Thomas Zwick (2013). "How selective are real wage cuts? A micro-analysis using linked employer-employee data". 88.

Hornstein, Andreas, Per Krusell, and Giovanni L. Violante (2011). "Frictional Wage Dispersion in Search Models: A Quantitative Assessment". *The American Economic Review* 101.7, 2873–2898.

Ibsen, Rikke, Trevisan Elisabetta, and Niels Westergaard-Nielsen (2008). "Job Mobility and Skill Transferability. Some Evidences from Denmark and a Large Italian Region". mimeo.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan (1993). "Earnings Losses of Displaced Workers". *The American Economic Review* 83.4, 685–709.

Jarosch, Gregor (2014). "Searching for Job Security and the Consequences of Job Loss". mimeo.

John T. Addison Paulino Teixeira, Thomas Zwick (2010). "German Works Councils and the Anatomy of Wages". *Industrial and Labor Relations Review* 63.2, 247–270.

Jovanovic, Boyan (1979). "Job Matching and the Theory of Turnover". *Journal of Political Economy* 87.5, 972–990.

Jovanovic, Boyan and Yaw Nyarko (1995). "The transfer of human capital". *Journal of Economic Dynamics and Control* 19.5, 1033 –1064.

Jun, Tackseung and Lalith Munasinghe (2005). *Does Wage Volatility Matter in Labor Markets? Theory and Evidence on Labor Mobility*. Working Paper.

Kahn, Lisa and Fabian Lange (2014). "Employer Learning, Productivity, and the Earnings Distribution: Evidence from Performance Measures". *The Review of Economic Studies* 81.4, p. 1575.

Kahn, Shulamit and Harriet Griesinger (1989). "Female Mobility and the Returns to Seniority: Should EEO Policy Be Concerned with Promotion?" *The American Economic Review* 79.2, 300–304.

Kambourov, Gueorgui and Iourii Manovskii (2004). "Occupational Mobility and Wage Inequality".

Katz, Harry C. (1993). "The Decentralization of Collective Bargaining: A Literature Review and Comparative Analysis". *Industrial and Labor Relations Review* 47.1, 3–22.

Kim, Marlene (1999). "Where the Grass Is Greener: Voluntary Turnover and Wage Premiums". *Industrial Relations: A Journal of Economy and Society* 38.4, 584–603.

Klaauw, Bas van der and António Dias da Silva (2011). "Wage dynamics and promotions inside and between firms". *Journal of Population Economics* 24.4, 1513–1548.

Klosterhuber, Wolfram, Jörg Heining, and Stefan Seth (2014). "Linked-employer-employee-data from the IAB: LIAB longitudinal model 1993-2010 (LIAB LM 9310)". 201308.

Lamadon, Thibaut, Elena Manresa, and Stephane Bonhomme (2015). *A Distributional Framework for Matched Employer Employee Data*. 2015 Meeting Papers 1399. Society for Economic Dynamics.

Leonardi, Marco and Giovanni Pica (2013). "Who Pays for it? The Heterogeneous Wage Effects of Employment Protection Legislation". *The Economic Journal* 123, 1236–1278.

Liu, Kai (2015). *Wage Risk and the Value of Job Mobility in Early Employment Careers*. IZA Discussion Papers 9256. Institute for the Study of Labor (IZA).

Lluis, Stéphanie (2005). "The Role of Comparative Advantage and Learning in Wage Dynamics and Intrafirm Mobility: Evidence from Germany". *Journal of Labor Economics* 23.4, 725–767.

Low, Hamish, Costas Meghir, and Luigi Pistaferri (2010). "Wage Risk and Employment Risk over the Life Cycle". *American Economic Review* 100.4.

Macho-Stadler, Inés, David Pérez-Castrillo, and Nicolás Porteiro (2014). "Coexistence of long-term and short-term contracts". *Games and Economic Behavior* 86.Supplement C, 145 –164.

Manacorda, Marco (2004). "Can the Scala Mobile Explain the Fall and Rise of Earnings Inequality in Taly? A Semiparametric Analysis, 1977-1993". *Journal of Labor Economics* 22, 585–613.

Maria Symeonaki, Glykeria Stamatopoulou and Maria Karamessini (2014). "On the Measurement of Early Job Insecurity in Europe".

Mazzocchi, Giancarlo (1981). "UNEMPLOYMENT IN ITALY AND EUROPE IN THE 1980s". *Giornale degli Economisti e Annali di Economia* 40.5/6, 363–370.

McLaughlin, Kenneth J. (1991). "A Theory of Quits and Layoffs with Efficient Turnover". *Journal of Political Economy* 99.1, 1–29.

Mincer, Jacob (1986). *Wage Changes in Job Changes*. Working Paper 1907. National Bureau of Economic Research.

Mincer, Jacob and Boyan Jovanovic (1979). "Labor Mobility and Wages". Working Paper Series 357.

Munasinghe, Lalith (2000). "Wage Growth and the Theory of Turnover". *Journal of Labor Economics* 18.2, 204–20.

Nagypál, Éva (2007). "Learning by Doing vs. Learning About Match Quality: Can We Tell Them Apart?" *The Review of Economic Studies* 74.2, 537–566.

Neal, Derek (1999). "The Complexity of Job Mobility among Young Men". *Journal of Labor Economics* 17.2, 237–61.

Papageorgiou, Theodore (2013). "Learning Your Comparative Advantages". *The Review of Economic Studies*.

Perticara, Marcela (2004). "Wage Mobility Through Job Mobility". 204.

Pfeifer, Christian and Stefan Schneck (2012). "Relative Wage Positions and Quit Behavior: Evidence from linked Employer-Employee Data". *Industrial and Labor Relations Review* 65.1, 126–147.

Pinheiro, Roberto and Ludo Visschers (2015). "Unemployment risk and wage differentials". *Journal of Economic Theory* 157, 397 –424.

Postel-Vinay, Fabien and Jean-Marc Robin (2002). "The Distribution of Earnings in an Equilibrium Search Model with State-Dependent Offers and Counteroffers". *International Economic Review* 43.4, pp. 989–1016.

Prat, Julien (2006). "Job Separation Under Uncertainty and the Wage Distribution". *The B.E. Journal of Macroeconomics* 6.1, 1–34.

Samek, Manuela et al. (2013). "The effectiveness and costs-benefits of apprenticeships: Results of the quantitative analysis". *European Commission*.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender (2010). *The long-term impact of job displacement in Germany during the 1982 recession on earnings, income, and employment.* IAB Discussion Paper 201001.

Serafinelli, Michel (2013). "Good Firms, Worker Flows and Productivity". mimeo.

Solnick, Loren M. (1988). "Promotions, Pay, Performance Ratings and Quits". *Eastern Economic Journal* 14.1, 51–62.

Spilerman, Seymour (1972). "Extensions of the Mover-Stayer Model". *American Journal of Sociology* 78.3, 599–626.

Stevens, Ann Huff (2001). "Changes in Earnings Instability and Job Loss". *Industrial and Labor Relations Review* 55.1, 60–78.

Stiglbauer, Alfred et al. (2003). "Job Creation and Job Destruction in a Regulated Labor Market: The Case of Austria". *Empirica* 30.2, 127–148.

Tattara, Giuseppe and Marco Valentini (2010). "Turnover and Excess Worker Reallocation. The Veneto Labour Market between 1982 and 1996". *Labour* 24, 474–500.

Tattara, Giuseppe and Mario Volpe (1999). "Why leave wage work and become self-employed ? Independence, earnings or unemployment". 10780.

Tealdi, Cristina (2011). *How do employment contract reforms affect welfare? Theory and evidence.* MPRA Paper 33573. University Library of Munich, Germany.

Topa, Giorgio et al. (2016). *Job Search Behavior among the Employed and Non-Employed.* 2016 Meeting Papers. Society for Economic Dynamics.

Topel, Robert H (1991). "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority".
Journal of Political Economy 99.1, 145–76.

Topel, Robert H. and Michael P. Ward (1992). "Job Mobility and the Careers of Young Men". *The Quarterly Journal of Economics* 107.2, 439–479.

Zweimüller, Josef et al. (2009). *Austrian social security database.* IEW - Working Papers 410. Institute for Empirical Research in Economics - University of Zurich.