Separations on the Job Ladder *

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November 30, 2019

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 percentage points above or below the median coincides with roughly 30% higher odds of job separation. The pattern 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

*The author thanks Robert Shimer, Harald Uhlig, Stéphane Bonhomme, Thibaut Lamadon, Elena Manresa, Elisa Giannone for helpful comments and discussions. In addition, the author would like to acknowledge helpful comments from seminar participants at the Applied Macro and Capital Theory Working Groups as well as participants at the Midwest Search and Matching Workshop. The author equally thanks UC Berkeley for their hospitality at the FDZ data center and the University of Chicago for their support for data access. Discalimer: This study uses (among other data sets) the Linked-Employer-Employee Data (LIAB) [LIAB LM 9310] from the IAB. Data access was provided via on-site use under project number fdz1012 at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB), in guest visits at UC Berkeley and UCL and remote data access.

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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 and studies its welfare consequences.

Using matched employer-employee data for three European countries, I detail and explain a previously undocumented U-shape pattern between wage changes and separations; that is, above and below median on-the-job wage growth 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 30%. Hence, workers experiencing both wage rises and wage declines face an increased likelihood of job separation.

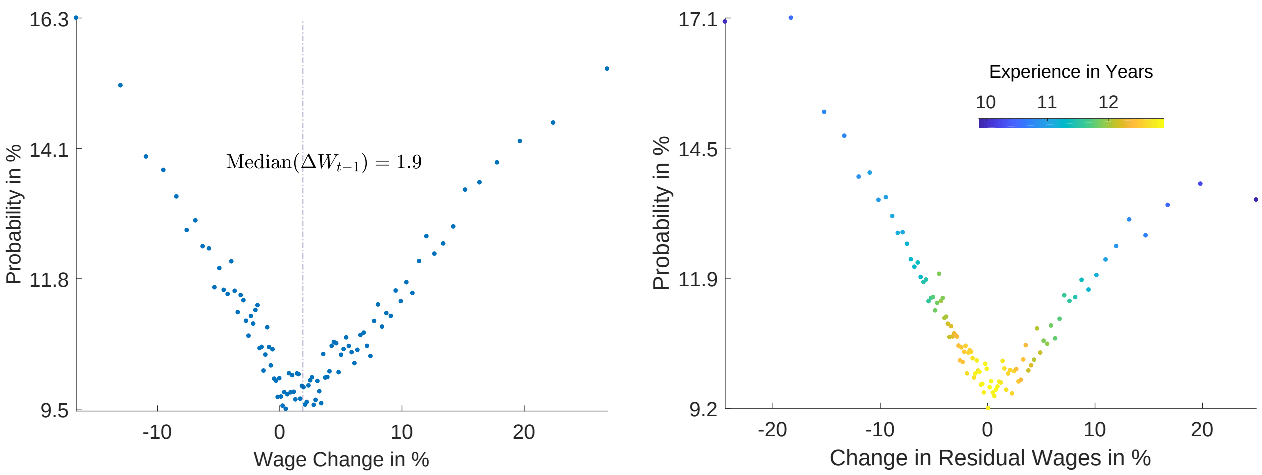


Figure 1: U-Shape relation between wage growth and separation propensity (Italy)

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

[1] cf. Topel and Ward (1992)

mechanisms account for the decline of the variance of wage changes in the model. First, the volatility of wage changes falls as workers are increasingly certain about their productivity. Second, workers can partially reduce their exposure to productivity shocks by accumulating renegotiation capital through on-the-job search. Third, 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. First, it highlights the reinforcing nature of young workers' wage instability. 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.Second, the U-shape pattern allows us to study the varying importance of different sources of income instability over the life cycle. In fact, I find a change in the relationship between wage changes and separations with experience. As a result, the U-shape pattern carriers more information than is contained in the simultaneous decline of separations and the volatility of wages. The theoretical model allows me to show that young workers are mainly exposed to (inescapable) wage instability related to their own ability, whereas older workers face job-specific and therefore avoidable income fluctuations. Furthermore, income instability through on-the-job wage changes reflects young workers' pervasive uncertainty about their own and match-specific productivity. This uncertainty comes with a significant economic cost. In the theoretical model laid out in this paper, workers with high wage instability also suffer from the highest inference errors in evaluating current match productivity. These workers are therefore more prone to incur wage losses due to suboptimal mobility patterns, either by leaving good matches or by staying in low quality matches. The U-shape pattern hence indicates match misallocation in the economy. Finally, the paper shows that wage change variability declines with average firm quality even after controlling for experience. I thereby present a novel dimension of increasing job quality on the job ladder that is falling wage change variability. This research shows that relative wage stability is a feature of high quality matches. This channel further rationalizes a larger exposure of low tenure workers to firm-specific shocks, consistent with a number of empirical findings in the literature.

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 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

[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.

for separations once wage levels are taken into account.[3]. Models describing learning dynamics and their effect on occupational switching (cf. Groes, Kircher, and Manovskii (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, Kircher, and Manovskii (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 level of wage changes) 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 reducing 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

[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. Moreover, this model predicts a positive autocorrelation of wage changes, at odds with evidence in this and other research (Topel (1991), Topel and Ward (1992))

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 a partial 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 an apprenticeship system and a short-lived increase in the variance of productivity shocks on output in the economy. I show that output losses due to learning can be reduced significantly through apprenticeship shemes. I further find a strong negative effect of short-term increases in productivity shock variances on output.

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 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 data set LIAB contains a representative draw of German firms surveyed in the IAB establishment panel together with their associated workers, whereas the Italian and Austrian data sets are constructed around the universe of firms within a geographic region, either for two provinces in the North-East of Italy or for the territory of Austria. The Italian VWH 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)[4] 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 if those workers move out of the sampling provinces. The data set 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. For each worker, the VWH contains information on all employment spells during the year, including total real earnings and time worked at the job 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 information on the qualification at the job provides a partial control for education levels (cf. Galizzi and Lang (1998)). I construct weekly wages using total real 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 6.3.5 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.

2.3 German LIAB

The linked employer-employee dataset LIAB[5] 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

[4] For further description of the data, refer to Tattara and Valentini (2010), Leonardi and Pica (2013), Ibsen, Elisabetta, and Westergaard-Nielsen (2008), Grinza (2014), Bartolucci, Devicienti, and Monzón (2015), Serafinelli (2013).

[5] Further details on the data set can be found in Klosterhuber, Heining, and Seth (2014) and Fischer, Janik, Mueller, and Schmucker (2008) for a detailed description as well as Card, Heining, and Kline (2013), Hirsch and Zwick (2013), Addison, Bellmann, Schank, and Teixeira (2008), John T. Addison (2010), Addison, Teixeira, Stephani, and Bellmann (2015), Guetzgen (2007).

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.[6] 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.

2.4 Austrian AMDB

The Austrian AMDB dataset[7] 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.

2.5 Sample Selection

The sample is restricted to full-time work spells of male workers with at most 30 years of age at entry into the data set. This restriction aims at reducing measurement error of observed labor market experience. The lower age limit is set to 16 years. Apprentices and workers in training are excluded from the sample due to potential differences in work contracts. I further restrict attention to full-time spells with undetermined duration. The restriction to full-time work is crucial in this paper in that it reduces potential bias caused by differences in hours worked. Especially for young workers with variable attachment to the labor force,

[6] 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.

[7] For a description of the data set, cf. here. For additional information, consider Zweimüller, Winter-Ebmer, Lalive, Kuhn, Wuellrich, Ruf, and Büchi (2009) and Borovickova (2013) using a similar data set.

reductions in earnings could in fact reflect reductions in hours worked. In the likely case that increases in hours worked manifest increasing attachment to the labor force, a negative relationship between changes in earnings and separations could simply reflect variations in labor market attachment. 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 6.3.6. For cases of multiple observations at one firm during a single year, I compute a weighted single wage observation.[8]

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, Wachter, and Bender (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 in order 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, thereby also following the convention in Topel and Ward (1992). 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 might have a higher likelihood of carrying measurement error which would increase observed wage change variance during years of separation. As a consequence, my results have to be understood conditional on t least two previous years of tenure. Figure 2 represents the timing in the data. For a worker in firm A, I require at least

[8] 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.

two full year observations to compute ΔW_{t-1}.[9] The object of interest is the probability of separating conditional on ΔW_{t-1}. Note that this timing convention also follows Liu (2015). Wage changes are computed as differences of log wages. Finally, I limit my attention to the 98% of the support of wage changes. Due to potential measurement error in the reporting of paid 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 6.3.5).
I conduct a number of robustness exercises to examine the effect on sample selection on my results. Specifically, I do not find qualitative differences when delaying the start date of the data set, when including apprentices or when using the arc percentage of wage changes rather than the log difference (cf. Appendix 6.3).

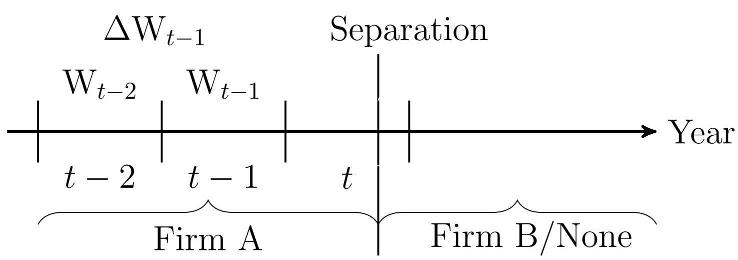


Figure 2: Timing in the empirical analysis

The figure shows the timing convention retained for the empirical analysis. The analysis estimates the conditional probability of job separation given the wage change between periods $t-1$ and $t-2$ before the year of potential separation.

2.6 Sample Description

Table 7 and 8 (cf. Appendix) summarize 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%.

[9]This requirement induces an unavoidable sample selection of spells that pertain for at least 2 years. In section 6.3 I discuss that I do not find evidence for this to bias my results.

These numbers compare well to the literature. Using the European Union's Labour Force Survey for 2014, Symeonaki, Stamatopoulou, 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 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 for the period 1985-1996 (compared to a mean of 1.85 in our sample). Similarly, Anger (2011) finds average wage growth rates of around 2-2.4% for the period 1984-2005 in Germany for workers aged 20-60.[10]

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.[11] In this approach I do not control for covariates. Second, I estimate a logit model

[10] Fuchs-Schündeln, Krueger, and Sommer (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.

[11] 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.

on the set of grid points. 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 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 $\Delta\mathrm{W}_{i,j,t-1}$ is obtained as

$$\Pr(\text{Separation}_k = 1) = \frac{1}{N_k}\sum_{i=1}^{N_k} I_{\Delta\mathrm{W}_{i,j,t-1}\in k}\text{Separation}_{i,j,t}$$

where $I_{\Delta\mathrm{W}_{i,j,t-1}\in k} = 1$ if $\Delta\mathrm{W}_{i,j,t-1} \in$ bin k. I obtain the logit specification as

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

The linear probability model instead is

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

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 coinicides with a separation probability of about 2 percentage points above the median separation rate in the case of Italy. Similarly, this case represents a change in the odds of separating of roughly 30%.[12] The difference in separations is statistically significant and economically meaningful. For instance, the difference in the separation rate between workers with 10 percent higher or lower wage changes compares to the difference in the separation rate observed after a reduction in the aggregate unemployment rate of 1% (cf. Haltiwanger, Hyatt, Kahn, and McEntarfer (2017) for the US). In figure 4, I report the logit specification for residual wage growth (cf. also Appendix table 9 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 wage changes.

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 narrow down the identification 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 refine this definition of layoffs. 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

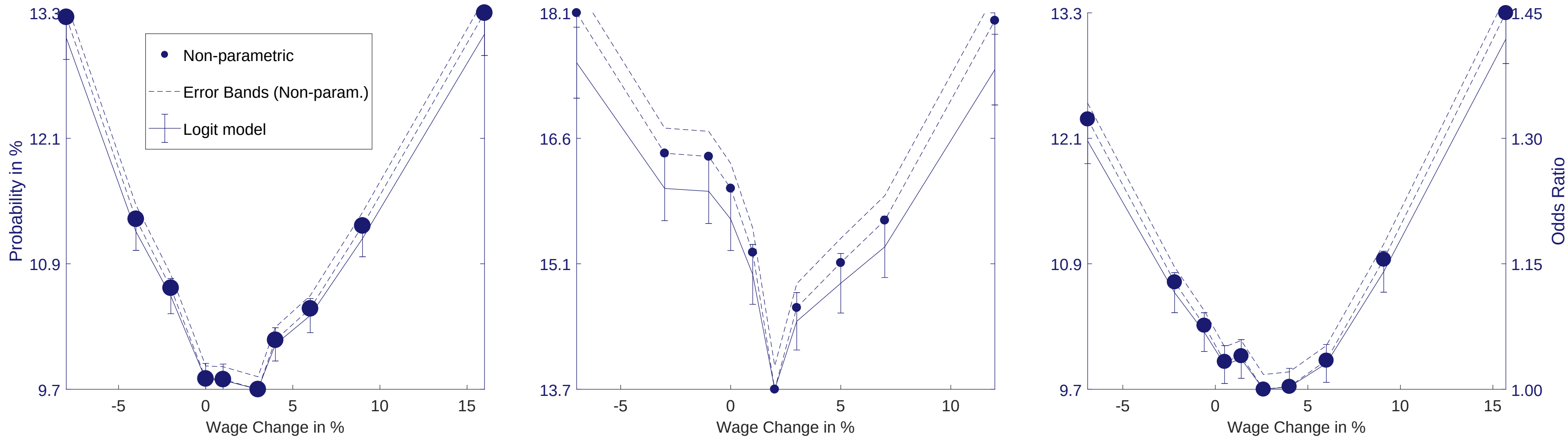
[12]For ease of interpretation, recall that the odds ratio is defined as $\frac{p_k}{1-p_k}/\frac{p_b}{1-p_b} = \frac{p_k}{p_b}\frac{1-p_b}{1-p_k}$ where p_b is the probability of separating at the median category and p_k the probability of separating within bin k .

requesting benefits for the first time[13]. As the sample selects workers that have worked 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 10, I estimate the linear probability model 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, Kircher, and Manovskii (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). 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 11 in Appendix). As the cited authors, I do find a (weak) U-shape relationship for all three datasets (cf. figure 14 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

[13]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 paid social security contributions for at 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). This definition of layoffs does not take into account the fact that quitters are also eligible to unemployment benefits in Germany and Austria after a suspension period. Precisely, quitters are suspended for 12 weeks (4 weeks) in Germany (Austria) if no attenuating circumstances apply (such as health and security reasons). I have conducted a robustness exercise by defining layoffs as instances in which workers receive unemployment benefits at the latest 1 week after the end of the work spell and did not find qualitatively different results. I also considered a definition of layoffs using information on benefit suspension at the beginning of a non-employment spell in the German dataset and did not find either significantly different results.

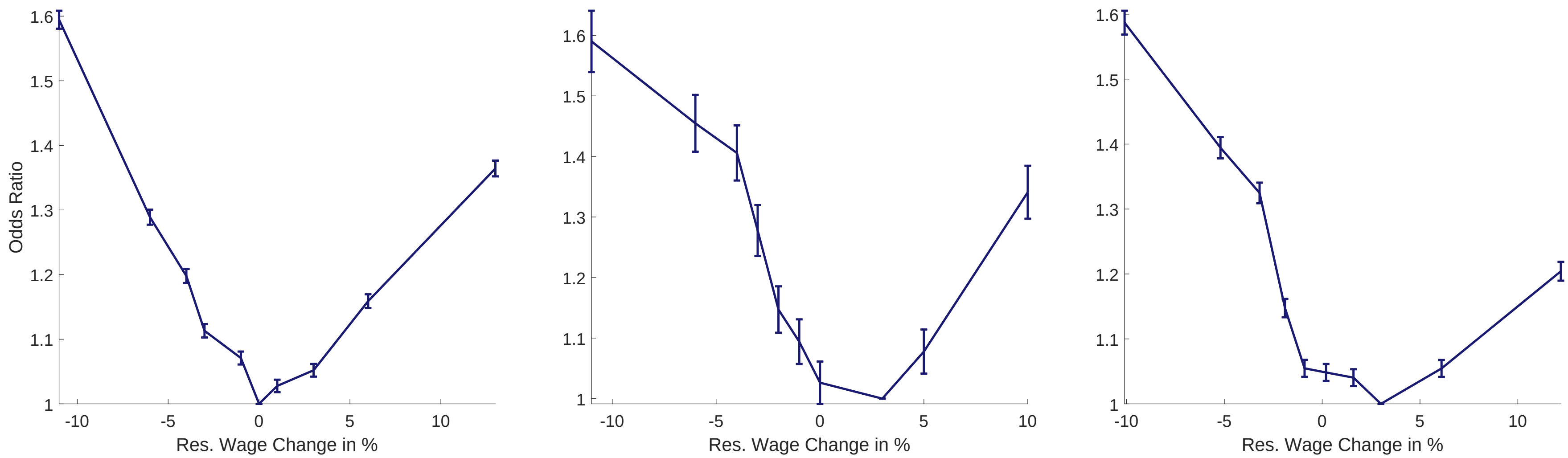
for Italy, I find that workers on average move to firms with higher wages. I hence conclude that occupational switching, that would predict movements to firms with on average lower wages for those workers with declining wages, is not the dominant driver of the observed pattern.



(a) Italy (b) Germany (c) Austria

Figure 3: U-shape relation between wage growth and separation propensity (All)

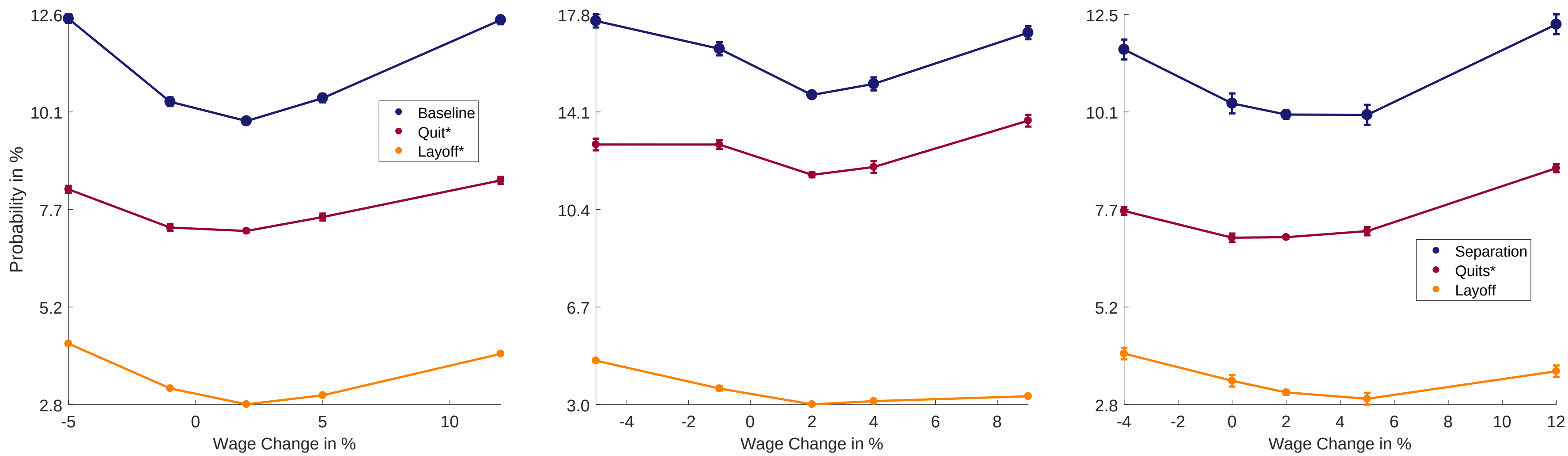
The figure shows the separation rate of workers at time t as a function of the change in wages at time $t-1$ as a non-parametric within-bin estimate (left axis) and in terms of the odds ratio of separating with respect to the median wage change bin (right axis). The right hand axis is aligned across 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: U-shape relation between residual wage growth and separation propensity (All)

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.



(a) Italy (b) Germany (c) Austria

Figure 5: Differences after separation (All)

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.

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.

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

In this specification, I further control for the size of the firm, the firm growth rate in terms of full time employees, and the wage level. The results are shown in table 1. 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 1 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 firm shocks as in Borovickova (2013). The specification further controls for lagged firm size and lagged tenure.[14] To address concerns about measurement 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 are quantitatively similar.[15] 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

[14] 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.

[15] 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.

	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 1: Experience effect on U-shape pattern

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

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

where $\text{Exp.}^{L,H}_{i,j,t-1}$ and $\text{Ten.}^{L,H}_{i,j,t-1}$ 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 samples. 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[16].

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 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 productivity[17] , they also ascend on the job ladder by moving to more productive firms.

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 implications of the framework.

[16]One might be concerned that risk preferences drive the results in the data. In Appendix 6.5, I use the US NLSY79 to examine this and do not find evidence for risk preferences to affect the U-shape pattern sizeably. Moreover, studying this dataset allows me to provide more direct evidence for the effect of skill uncertainty in addition to providing the baseline result for US data.

[17]This framework focuses on learning about the productivity of a 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 6.11 I argue that learning of skills is not a dominant channel in Italy and Austria.

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 $\tilde{\beta}$. 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 with mean zero and standard deviation σ^2. The logarithm of the output process $y_{i,j,t}$ is described as

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

In light of the empirical evidence that suggests that occupational switching is not the main driver of the observed pattern, I do not model differences in skill complementarity across firms. This is further in line with the findings of Bonhomme, Lamadon, and Manresa (2015) who do not find strong evidence against additive worker/firm production specifications.

While firm productivity is common knowledge across all members of the economy, workers' productivity is not observed. Still, all learning in this economy is symmetric, that is all information on the worker's productivity is shared between workers and firms. Yet, by observing output, workers can learn about productivity.[18] 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 6.7 for details) as

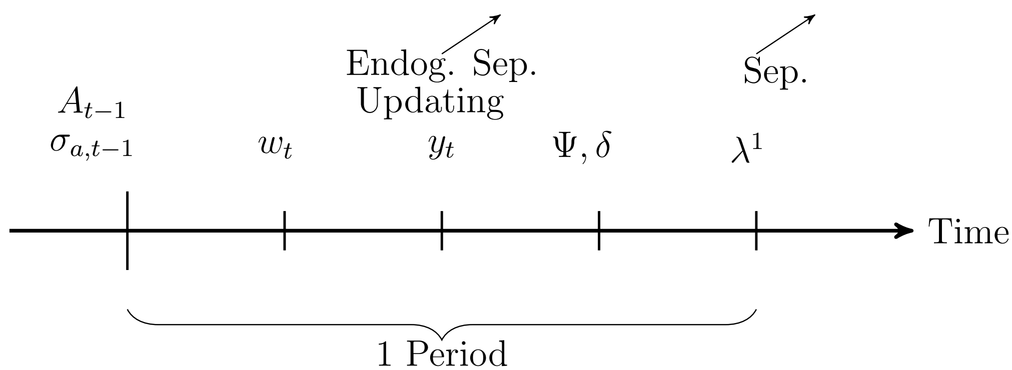
$$\sigma_{a,i,t}^2 = \frac{\sigma_{a,i,t-1}^2}{1 + s_{i,t-1}} \qquad\qquad A_{i,t} = A_{i,t-1} + \frac{s_{i,t-1}}{(1 + s_{i,t-1})}\xi_{i,j,t}$$

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

[18]Hence, workers do not learn about their type when unemployed. A generalization of the framework that would allow for learning when unemployed is 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.

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 and workers can exit the labor market permanently at rate Ψ. When unemployed, workers receive unemployment benefit z and search at rate λ_0 for new job offers.[19]

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. In the following, output is revealed and both the worker and the firm 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. Then the worker can be separated from the current match at the exogeneous rate δ or leave the labor market at rate Ψ. 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 y_t Output δ Prob. Ex. Layoff Ψ Prob. Death λ^1 Prob. Job Offer

Figure 6: Timing in the theoretical model

The figure shows the timing convention retained in the theoretical model. At the start of the period, workers and firms hold beliefs $A_{t-1}, \sigma_{a,t-1}$. After wages are payed and output is realized, workers potentially endogeneously separate and update their beliefs. Workers can then separate exogenously due to layoff or death or endogeneously due to an attractive outside offer.

[19] This model does not allow for endogeneous search effort as in Topa, Sahin, Mueller, and Faberman (2016). Allowing for endogeneous search effort would likely 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, Sahin, Mueller, and Faberman (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 and for simplicity of exposition, 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 $\int U(I') - U(I)dG(I')$. 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

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

where $S^+(J, I) = \max\{S(J, I), 0\}$ and $\beta = \tilde{\beta}(1 - \Psi)$. Moreover, the worker's value of unemployment is

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

For a given shock distribution G, 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 $W(J, I)$ 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 about worker's ability. 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 6.8 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 the same for all workers due to linearity of the production framework. Hence, the arrival of random job offers at a fixed rate together with a fixed firm type distribution implies that the likelihood of the arrival of higher valued job offers declines as agents move up the job ladder.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 of a negative effect of tenure on separations.

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 2. 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%. Given an average labor market history of 30 years, I calibrate the factor β as .92. 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).

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

Table 2: Overview model parameters (baseline model)

I calibrate the eight parameters to fit a set of moments as described in table 3. First, I 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 $\text{Var}[A_0]$, the true variance of abilities $\text{Var}[a_i]$ and the variance of productivity shocks σ^2 (cf. Appendix 6.8). 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 $E(W_{t-1})^3$.[20]. These moments inform the belief variances as well as the firm and worker 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 $\hat{\mu}(\text{Sep})$ as well as the separation rate

[20]These are obtained, as standard, as

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

for experienced agents with 16 years of experience $\hat{\mu}(\text{Sep})_{X=16}$. The empirical counterpart for experienced 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 5 summarizes the empirical and simulated moments. Table 4 collects the calibrated parameters.

#	Moment	Description	Data (IT)	Model
1	$\hat{\mu}(\text{Ten.})$	Mean Tenure (Years)	6.9	6.3
2	$E(W_{t-1})^3$	Skewness W	0.7	0.7
3	$E(\Delta W_{t-1})^3$	Skewness ΔW	0.5	0.5
4	$\hat{\sigma}(\Delta W_{t-1})$	Std. ΔW $\times$ 100	6.9	6.9
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 $\times$ 10	3.2	3.1
7	$\hat{\mu}(\text{Sep})$	Mean Sep. Rate %	11.9	10.4
8	$\hat{\mu}(\text{Sep})_{X=16}$	Mean Sep. Rate Exp. 16 %	8.2	7.5
9	$z/\mu(W_{t-1})$	Replacement Rate %	50	49

Exp. denotes years of experience

Table 3: Overview moments (baseline model)

Parameter	Description	Value
	Productivity and Types	
$E[\mu_j], \text{Var}[\mu_j]$ (Log-Normal Distr.)	Dist. Firm Prod.	[.010, .0028]
σ^2	Volatility Shocks	.0153
$\text{Var}[A_0]$ (Normal Distr.)	Var. 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	
β	$\beta = (1/(1+r))(1-\Psi)$	0.92
z	Unemployment Flow	0.5

Table 4: Calibrated parameters (baseline model)

The calibrated job finding rates are higher in levels than the estimates found for instance in

Jarosch (2014), yet their ratio is almost identical with the one obtained there. 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.

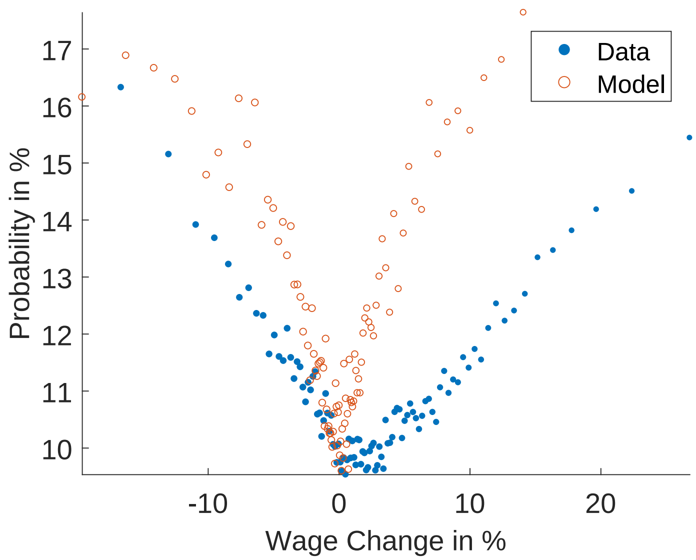


Figure 7: Empirical data and simulation results (baseline model)

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 such that output is now defined as

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

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 belief updating formula due to initial match productivity being zero.

Autocorrelation in match-specific productivity changes the learning process slightly (cf. Appendix 6.7). 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 expected output

$$\Delta W_t = \Delta E[Y_{i,j,t}]$$

(cf. Appendix section 6.9 for details). This implies that the variance of wage changes and the autocovariance of wage changes are a function of the variance of shocks to dynamic productivity and of the autocorrelation of match productivity. Specifically, in the absence of surplus sharing ($\alpha = 1$), the variance of wage changes will decline with experience and converge to the variance of realized dynamic match productivity. Moreover, wage changes converge to changes in realized dynamic match productivity (cf. Appendix 6.8). Due to the latter's autoregressive structure, this setting hence allows for a negative autocorrelation of wage changes.

However, the extension does not only alter the wage distribution but also affects separations in the model. First, given the known initialization of match productivity at new spells, negative productivity shocks can lead to separations. Second, in the presence of learning, the belief about match productivity N_t is affected by the uncertainty about a worker's type. As I will discuss in section 4.7.2, this will lead of suboptimal mobility patterns in the model. Crucially, adding match-specific productivity allows for a feedback effect between learning and separations. Separations lead to learning gains due to re-initialization of match-specific productivity at zero (and hence a one-time information shock). This in turn reduces the variance of wage changes. Differently from the basic model, allowing for match-specific productivity therefore introduces a causal feedback mechanism between the variance of wage changes and separations.

4.5.2 Wage Renegotiation

Furthermore, 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. 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 $V(J, I, O, M) - U(I)$ equals

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

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 6.6. The surplus of worker I at firm J with current match productivity M is then

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

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. Given the surplus sharing rule and the value of the match to the worker, knowledge of $S(J,I,M)$ allows to compute the wage $W(J,I,O,M)$ (cf. Appendix section 6.6 for details).

$$
\begin{aligned}
W(J,I,O,M) &= SS(J,I,O,M) + z - \Big(\beta \int U(I') - U(I) dG^J(I') + \beta(1-\delta) \\
&+ \lambda^1 \Big(\int_{\mathcal{M}_2} \int_{\mathcal{M}_1} SS(J',I',J,M^0) dF(J') dG^J(I') \\
&+ \int_{\mathcal{M}_2} \int_{\mathcal{M}_3} SS(J,I,J',M') dF(J') dG^J(I') \Big) \\
&+ \int_{\mathcal{M}_2} \Big(1 - \lambda_1 \int_{\mathcal{M}_1 \cup \mathcal{M}_3} dF(J') \Big) \mathrm{Mx} dG^J(I') \Big) \\
&+ \beta \lambda^0 \alpha \int_{\mathcal{M}_1} S(J',I,M^0) dF(J')
\end{aligned}
$$

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

To consider the impact of the surplus sharing rule on 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 received by 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 illustrates that variations in the bargaining weight determine the extend to which workers can avoid exposure to match specific productivity shocks by searching for outside options. 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 surplus from the match will reflect all 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 surplus share varies few with match specific productivity. However, high levels of a worker's surplus share imply that workers cannot evade instability due to match specific productivity. As a result, this extension contributes to the mechanism first by increasing the variance of on-the-job wage changes due to an additional channel for wage growth, and second by increasing instability for agents at low ranks of the job ladder. 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 $E[\sigma_j^2]$, variance $\mathrm{Var}[\sigma_j^2]$ 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 scenario. 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. Further note that allowing for differences in firm shock volatility introduces a new motive for separations. Yet, in the presence of productivity differences, these motives are largely overshadowed in this model.

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 $\mathrm{Var}[\sigma_j]$, 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.

As in the baseline model, the standard deviation of wage changes $\hat{\sigma}(\Delta W_{t-1})$ in the full model is a function of learning parameters and firm shock variances and match productivity autocorrelation ρ. Moreover, it is also affected by α, the bargaining weight of the worker. To further capture the firm-type distribution in the variance component, I consider both the average $\hat{\sigma}(\Delta W_{t-1})$ and the $\hat{\sigma}(\Delta W_{t-1})$ for workers observed after a period of unemployment. In my model, displaced workers restart at the bottom of the job ladder, whereas the average worker has had the opportunity to ascend the job ladder. 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 $\hat{\gamma}(1)_{\Delta W_{x=16}}$.[21] 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 $\widehat{\mu(W^0_{t-1})/\mu(W_{t-1})}$.[22] The empirical set of moments is collected in table 5. 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 in table 6. 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. Further, 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,

[21] The sample analogue is obtained as

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

[22] I compute $\widehat{\mu(W^0_{t-1})/\mu W_{t-1}}$ as

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

#	Moment	Description	Data	Model Baseline	Model All
1	$\hat{\mu}(\text{Ten.})$	Mean Tenure (Years)	6.9	6.4	6.3
2	$E(W_{t-1})^3$	Skewness W OJ	0.7	0.7	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	6.9	7.1
5	$\hat{\sigma}(W_{t-1})$	Std. W $\times$ 10	3.4	3.4	3.6
6	$\hat{\sigma}(W)_{X=4}$	Std. W Exp. 4 $\times$ 10	3.2	3.1	3.3
7	$\hat{\mu}(\text{Sep})$	Mean Sep. Rate %	11.9	10.4	10.6
8	$\hat{\mu}(\text{Sep})_{X=16}$	Mean Sep. Rate Exp. 16 %	8.2	7.5	8.3
9	$z/\mu(W)$	Replacement Rate %	50	49	49
		Targeted Only in Model (All)			
10	$\hat{\gamma}(1)(\Delta W_{t-1})_{X=16}$	AutoCorr. Exp. 16	-0.20	0.001	-0.20
11	$\hat{\mu}(W^0_{t-1})/\hat{\mu}(W_{t-1})$	Wage Ratio out of Unemp.	0.87	0.98	0.87
12	$\hat{\sigma}(\Delta W_{t-1})_{X=4}$	Std. ΔW Exp. 4 $\times$ 100	7.6	2.1	7.2
13	$\hat{\sigma}(\Delta W_{t-1})^d_{X=4}$	Std. ΔW Exp. 4,disp. $\times$ 100	8.1	2.2	8.4

Exp. denotes years of experience

Table 5: Overview moments (extended model)

the calibration shows an elevated exposure to shocks to match productivity. 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.[23] Overall, the fit of the model to the U-shape is improved, as can be seen in figure 8.

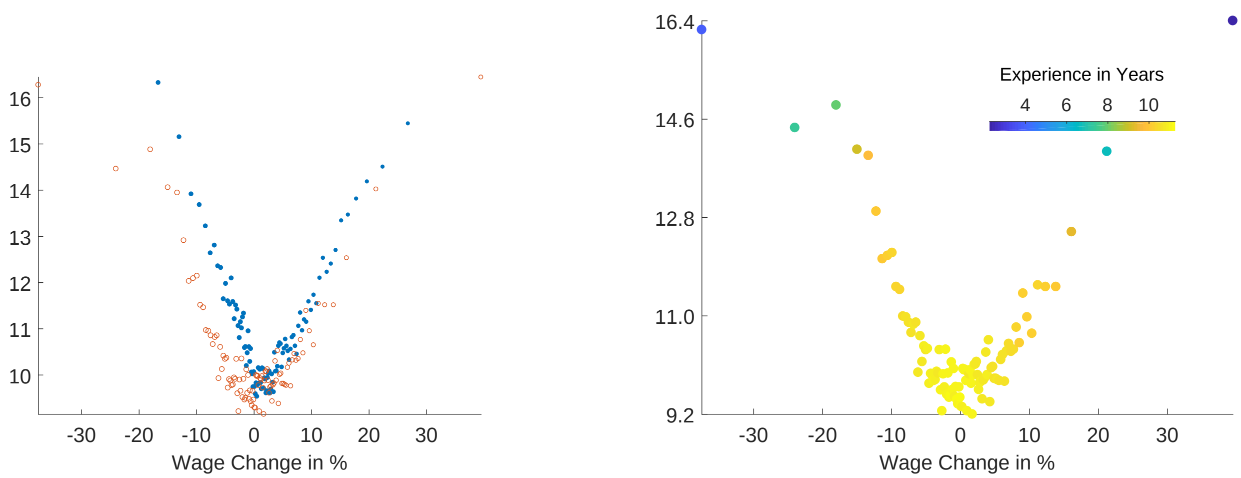


Figure 8: Empirical data and simulation results (extended model)

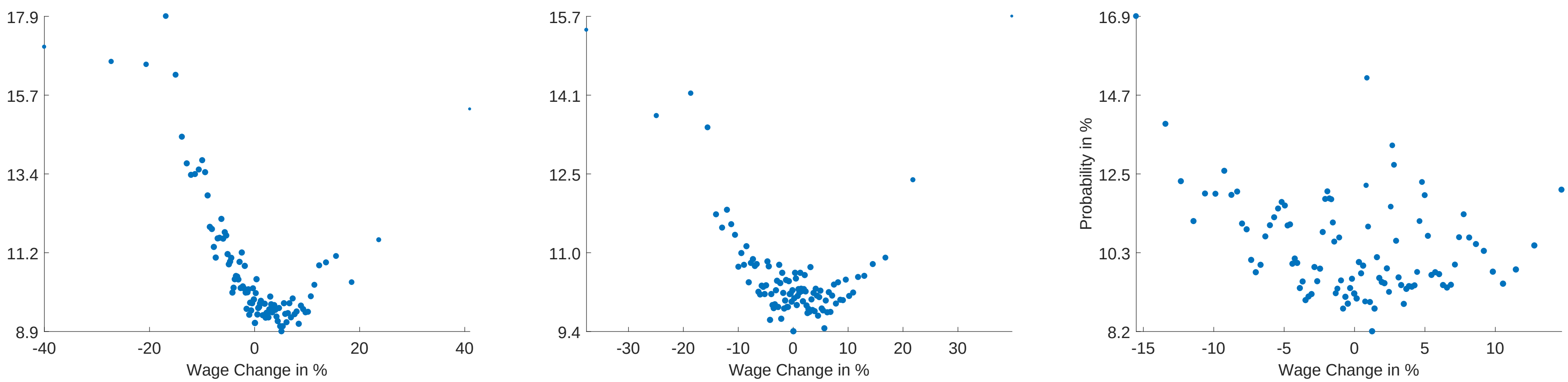
The left figure shows the empirical U-shape in blue together with the simulated U-shape in orange overlayed. On the right, I show the simulated U-shape and color-code the dots for their mean experience level.

[23]This estimate is in line with research on the relation of firm productivity and volatility. A line of research has studied the empirical correlation of firm size and the variability of sales or employment growth. The literature finds a negative relationship between the two (cf. for instance Yeh (2017)).

Parameter	Description	Value
	Productivity and Types	
$E[\mu_j], \text{Var}[\mu_j]$ (Log-Normal Distr.)	Marginal Dist. Firm Prod.	[-.8, 0.063]
$E[\sigma_j], \text{Var}[\sigma_j]$ (Log-Normal Distr.)	Marginal Distr. Volatility	[-3.81 0.01]
ρ_1(Correlation)	Correlation Firm Attributes σ_j, μ_j	-.85
ρ	Persistence Firm Shocks	0.61
$\text{Var}[A_0]$ (Normal Distr.)	Distribution Initial Belief Ability	[0.41]
$E[a_i],\ \text{Var}[a_i]$ (Normal Distr.)	Distribution True Ability	[0.67, 0.21]
	Labor Market	
λ^1	Offer Arrival Rate Employed	0.33
δ	Spontaneous Layoff Rate	0.03
α	Worker Bargaining Weight	0.69
λ^0	Offer Arrival Rate Unemployed	0.45
	Other	
β	$\beta = (1/(1+r))(1-\Psi)$	0.92
z	Unemployment Flow	0.5

Table 6: Overview parameters (extended model)

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 $\rho = 0.86$.



(a) $\rho' = .86$

(b) $\rho'_1 = 85$

(c) $\sigma'_{a0} = 0$

Figure 9: U-shape after 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 weaken the (core) U-shape. 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 is amplified by low in-sample correlations 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. [24] 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 supports the pattern.

Notice that this paper has given one possible interpretation to the autocorrelated part of match 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 the volatility of beliefs about productivity could in fact represent a learning technology of general skills with declining variance. This result therefore suggests 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.[25]

[24] 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.

[25] I have further assumed individual specific productivity to be constant in time. One could have instead assumed dynamic (unobserved) worker ability. The main difference in this case as compared to the specifi-

4.7 Implications

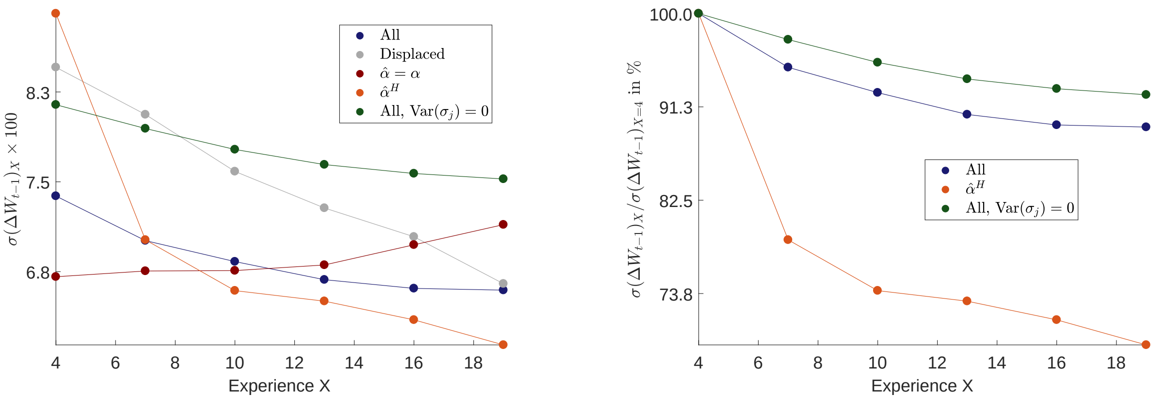
In the following, I discuss the effect of the firm type distribution and learning and show how both affect output in this economy. Specifically, I show how learning affects inference about match quality, thereby reducing aggregate output due to suboptimal mobility. The job ladder alleviates part of these losses by allowing for more rapid learning at higher rungs of the ladder.

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. Third, 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 on the volatility of wage changes in the calibrated model, I separately consider the variance of wage changes for workers with different levels of negotiation capital and for workers at different levels of the job ladder. In Figure 10, I show the experience profile of the standard deviation of wage changes and how it is affected by renegotiation and the firm type distribution. Specifically, I consider the variance of wage changes for displaced workers. These workers have been unemployed for at least one period before randomly matching with a firm, such that they have no negotiation capital and could not ascend the job ladder yet. The variance of wage changes for these workers is therefore elevated and up to 15% higher than the average $\sigma(\Delta W_{t-1})$. Yet most of this difference is driven by the firm type distribution, as can be see when considering workers with the same negotiation capital but at firms with on average higher productivity. To measure negotiation capital, I compute the worker's share of surplus $\hat{\alpha} = (1-\alpha)S(O, I, M^0)/S(J, I, M) + \alpha$ and consider workers with the same negotiation capital as displaced workers ($\hat{\alpha} = \alpha$). These workers have lower volatility at low experience but higher volatility at higher levels of experience as compared to the average worker. The opposite is true for workers with high negotiation capital ($\hat{\alpha} \geq .99$). This result is consistent with empirical evidence for the US showing that

cation presented above concerns the output losses due to learning. In the case of dynamic worker ability, the estimation error of match specific productivity would decline with experience but not all the way to zero, such that aggregate output losses due to learning are expected to be higher. Assuming no dynamic match productivity and only dynamic worker ability, however, would be inconsistent with the empirical fact that separations decrease both with tenure and experience.



(a) $\sigma(\Delta W_{t-1})$

(b) Rel. $\sigma(W_{t-1})$

Figure 10: Experience profile $\sigma(\Delta W_{t-1})$

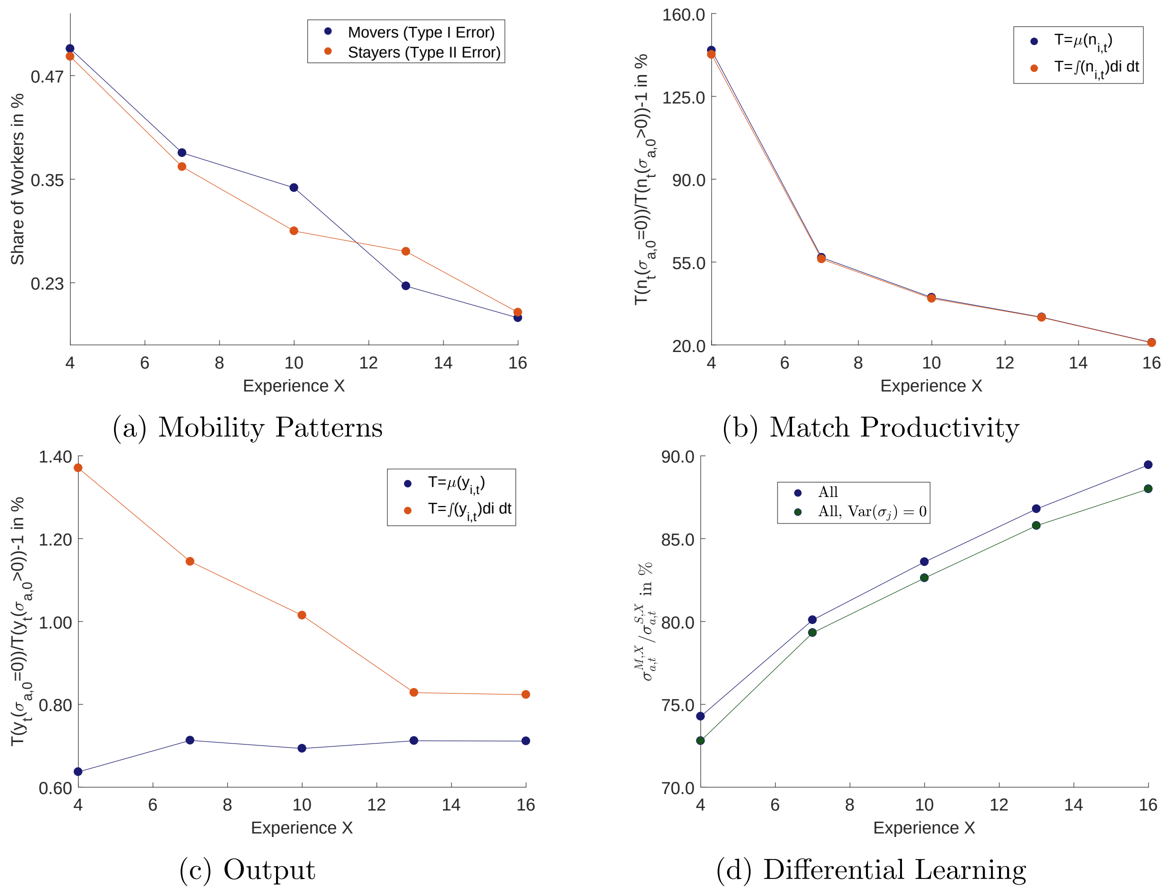
The left figure shows the time path of $\sigma(\Delta W_{t-1})$ at experience level X, the right figure shows the same time path of $\sigma(\Delta W_{t-1})$ relative to the value at experience level 4.

experienced displaced workers face higher income instability up to several years after the displacement (cf. Stevens (2001)).

The right panel shows the variance path relative to $\sigma(\Delta W_{t-1})$ at experience of 4 years. It shows that in fact the decline in the variance of wage changes is a result of the firm type distribution; when allowing firms to differ in the volatility of wage changes, volatility declines faster. Moreover, renegotiation also contributes to a faster decline in the volatility of wage changes. In summary, this analysis has demonstrated that the decline in the variance of wage changes is enhanced by the firm type distribution.

4.7.2 The effect of learning

Learning affects not only the volatility of wage changes but also mobility and production in the economy. First, error prone evaluations of match productivity lead to suboptimal mobility patterns as long as workers learn about themselves. Second, as match productivity is an experience good, young workers learn through separations, such that the uncertainty of beliefs falls after separations. This amplifies the experience effect on the U-shape. Figure 11 demonstrates these two implications of learning in the model. In the upper left panel, I plot the share of workers separating due to erroneous inference about match productivity in blue, obtained as cases that would sustain at least one more period if the true match quality was revealed. These are workers holding a job offer J' such that $S(J, I, n_t) > S(J', I, 0) > S(J, I, N_t)$. In this case, separations increase by up to half of a percent for young workers (out of on average 11 %). I also plot the corresponding type II error for workers staying despite low true match productivity (orange). As expected, both



(a) Mobility Patterns

(b) Match Productivity

(c) Output

(d) Differential Learning

Figure 11: Effect of learning

The upper left figure shows mobility patterns at experience level X in percent, once for erroneous moves (type 1) and once for erroneous stays (type 2). The upper right hand figure shows the effect of this mobility pattern on average and total match quality, compared to the case without learning. The lower left figure shows the same difference in average and total output. The lower right figure oulines the the ratio of the variances of beliefs for movers and stayers.

types of error are of roughly equal prevalence. Yet, in both cases, average match quality falls - either because good matches are destroyed or bad matches are sustained. This fact is depicted in the upper right panel which plots the ratio of the average and total match productivity in the case of no learning frictions as compared to the case with learning frictions. Match productivity, despite accounting for a small share of total output in this calibration, increases by up to 100% in the absence of information frictions. Overall, total and average output are lower in the case of learning than without learning by about 1.4%, as can be seen in the lower left panel, driven both by the extensive margin of a smaller employment rate and the intensive margin of lower match-specific productivity. In summary, learning reduces output in the model and reduces average match productivity, especially for young workers. Differently put, young workers have on average lower match quality than older workers due to the selection effect of unbiased mobility patterns for older workers.[26] The lower right panel depicts the relative uncertainty of a worker about his type for workers that moved the previous period relative to those that have not moved. The figure shows that stayers have up to 16% higher uncertainty about their type than movers. This result is not driven by the firm type distribution, as can be seen when considering the case when $\mathrm{Var}(\sigma_j) = 0$ but is a result of the updating equations.[27]

This analysis has shown that learning, together with dynamic match productivity, does in fact create a feed-back effect between learning, the variance of wage changes and separations. To further quantify the output effects, I consider the case of the welfare effects of an apprenticeship system. In the model, the sequencing of jobs is not insignificant due to learning. In fact, an apprenticeship system with the sole purpose of learning about a worker's type can lead to increased output overall. For instance, suppose all workers attended such an apprenticeship firm and let this firm have a shock volatility one standard deviation below the average firm at labor market entry. In the simulation, the aggregate output produced during the next 24 years after the apprenticeship exceeds the output produced during 25 years in an economy without apprenticeship system by 1%. Total match specific productivity increases by roughly 12%. This exercise highlights aggregate output effects of apprenticeship systems beyond the transmission of skills by increasing allocative efficiency and hence total output. Notice however, that this model also allows to reduce the effect of learning frictions through faster accession of the job ladder. To understand the effect of labor search, I increase the job finding rate by 10%. In this case, total output over 25 years labor market history increases by .4% as compared to the baseline, and total match productivity by 16%. This result shows that most of the losses in dynamic match productivity can be avoided through faster accession of the job ladder and effective quicker learning at higher ranks of the job ladder.

[26] In a model with additional types of shocks that are perfectly observed, as for instance aggregate productivity shocks, this would imply that young workers are on average more susceptible to suffer from endogenous layoff, all else equal. 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)). The fact that average match quality is higher for more experienced workers holds despite an increase in the variability of changes in N_t with experience, which makes larger falls in match productivity more likely. This is again a result of selection into productive matches. As the variance of ΔN_t increases as learning ensues, larger revisions in N_t are more likely. Yet, as workers are on average at better firms, these changes are also less relevant for separations, such that the separation rate due to changes in N_t still declines on average.

[27] This is obvious when considering that $\sigma_{a,t} = \frac{\sigma_{a,t-1}}{1+s}$ with $s = \sigma_{a,t-1}(1 - I_{OTJ}\rho)/\sigma_j^2$. Note however that this result is due to the assumption of zero initial match productivity. If instead we assumed that each match would start with some unobserved N_0, drawn from some distribution $N(n_0, \sigma_n^2)$, the initial variance updating would be $\sigma_{a,t} = \frac{\sigma_{a,t-1}(1+z)}{1+s+z}$, $z = \rho^2\sigma_n^2/\sigma_j^2$. As a result, $\sigma_{a,t}$ could rise instead after a move if $z > \frac{\rho(2-\rho)}{(1-\rho)^2}$. This requires a high value of σ_n^2. In the case of the calibrated ρ, one would require that σ_n^2 is more than 11 times as high as σ_j^2.

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	513	1050	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 7: 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 8: Summary Statistics II

6.2 Tables and Figures

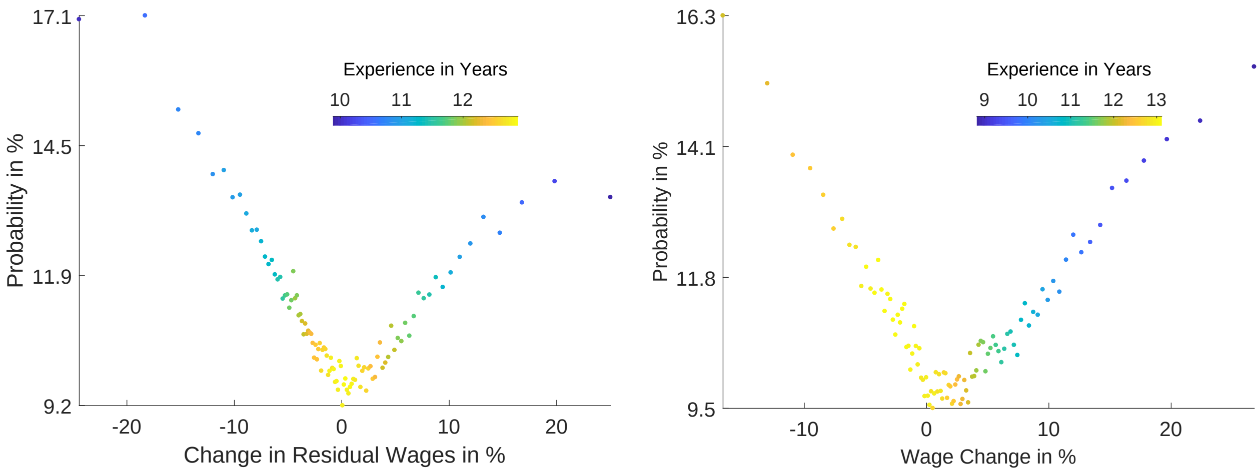


Figure 12: U-Shape between wage growth and separation propensity (Italy)

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 (right panel) and within centiles of the distribution of changes in residual wages (left 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 9: Overview specifications (baseline, residual, 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	0.13	0.02	0.0245	0.20	-0.084	-0.016	-0.016	-0.074
	(0.0036)	(0.0027)	(0.0021)	(0.009)	(0.009)	(0.009)	(0.005)	(0.0044)	(0.0029)	(0.0037)	(0.0031)
ΔW^2_{t-1}	1.41	0.53	0.74	1.95	1.21	1.01	1.80	1.25	0.53	0.77	0.73
	(0.023)	(0.017)	(0.014)	(0.075)	(0.069)	(0.069)	(0.043)	(0.027)	(0.018)	(0.023)	(0.019)
Constant	0.11	0.065	0.033	0.157	0.126	0.12	.04	0.10	0.048	0.071	0.049
	(0.00023)	(0.00018)	(0.00014)	(0.0005)	(0.0005)	(0.0005)	(0.00029)	(0.00026)	(0.00017)	(0.00022)	(0.00019)
Observations	2.3M	2.3M	2.3M	.6M	.6M	.6M	.6M	1.8M	1.8M	1.8M	1.8M

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

Table 10: Differences after separation

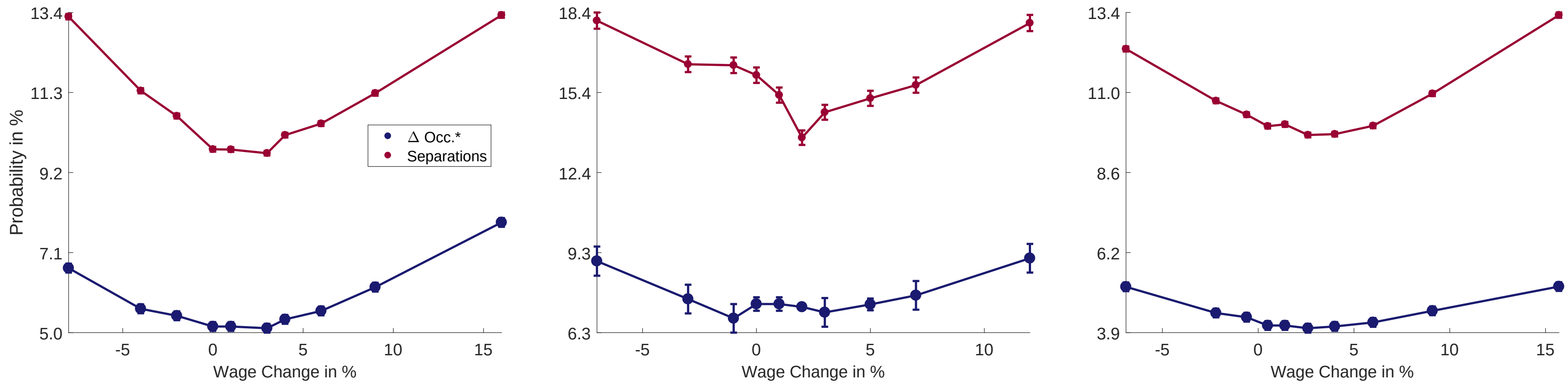
Column (a) contains the baseline specification for separations, column (b) contains quits, column (c) contains layoffs in the IT sample. In DE & AT sample, column(b) contains quitters with at most 2 months of non-employment, column (c) denotes quits as constructed as a reminder after accounting for received unemployment benefits, column (d) denotes layoffs as constructed through observed receipt of benefits. See text for details.

	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

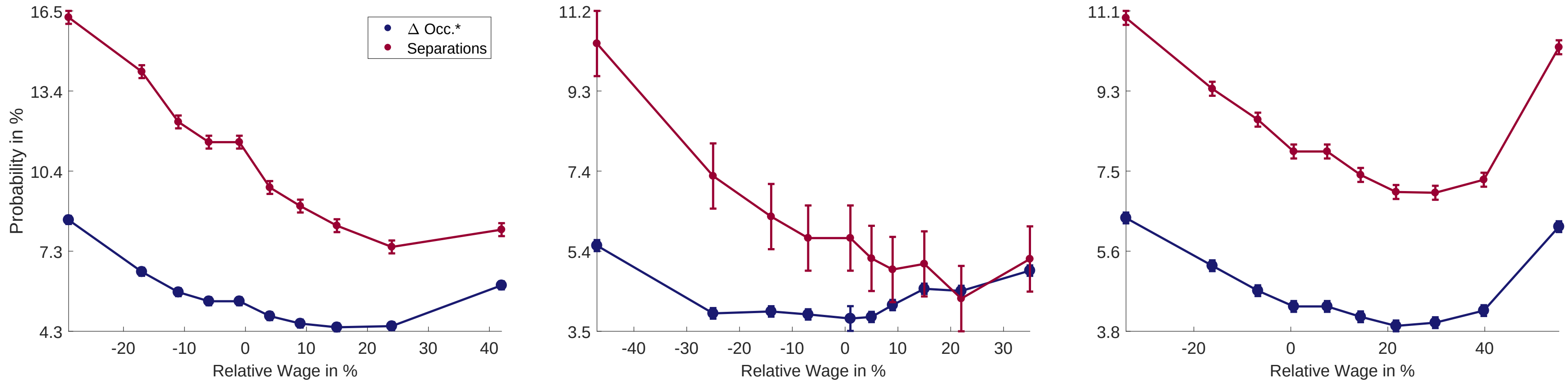
Table 11: Effect wage growth and relative position of a worker on U-shape pattern



(a) Italy (b) Germany (c) Austria

Figure 13: U-shape relation between wage growth and job mobility (All)

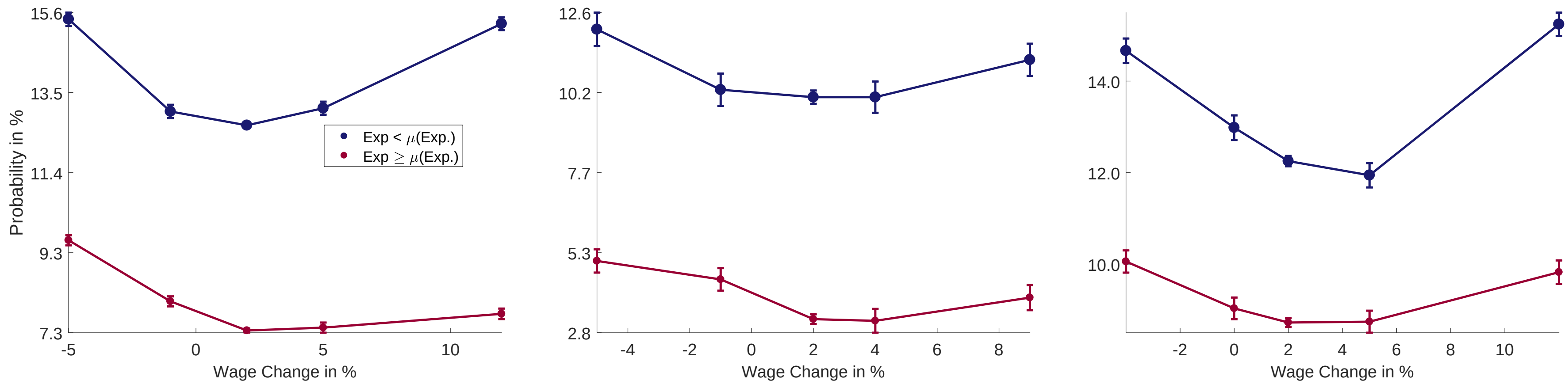
The figure shows the average separation rate and the average rate of occupational switching at time t for workers experiencing wage changes at time $t-1$ within deciles of the distribution of wage changes.



(a) Italy (b) Germany (c) Austria

Figure 14: Relation between relative wages and job mobility (All)

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.



(a) Italy (b) Germany (c) Austria

Figure 15: Experience effect on U-shape pattern (All)

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 on U-shape pattern 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 on U-shape pattern 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)
$\Delta W^2_{t-1} \times$	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 $\leq \mu(X)$	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$\times$ X, coefficients non-reported

Table 14: Experience effect on U-shape pattern IV

	Italy		Germany		Austria	
	Low	High	Low	High	Low	High
1st Quintile ΔW_{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 ΔW_{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 ΔW_{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 ΔW_{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: U-shape pattern by wage change volatility

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 16 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: Effect of delayed entry on U-shape pattern

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.[28] Finally, apprenticeship

[28] cf. Samek, Comi, Origo, and Torchio (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 17 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: Effect of including apprentices on U-shape pattern

6.3.3 Wage Growth

As discussed in Guvenen, Karahan, Ozkan, and Song (2016) and Davis, Haltiwanger, and Schuh (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, Haltiwanger, and Schuh (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.

	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)
$\Delta W_{t-1}^{\text{arc}}$		-0.086***		-0.086***		-0.023***
		(0.0036)		(0.0096)		(0.0043)
$(\Delta W_{t-1}^{\text{arc}})^2$		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: U-shape pattern with different wage growth measures

6.3.4 Spell Selection

The requirement of at least 2 years duration of a spell could potentially create selction bias in my sample. For example for Italy, this leads to a sample with on average older workers with higher labor market experience, consistent with an evolution towards more stable employment relationships as discussed in Topel and Ward (1992) (cf. table 19). Theoretically, this could also lead to a selection of spells with high enough previous wage changes to be sustained. As a result, I would observe only spells that previously had high wage changes. This effect is unlikely given the data for Italy. In table 19, I show that workers separating after two full years of work have on average higher wage changes than workers that stayed in the job at that time. Further, this selection is not worrisome for my theoretical analysis that builds on the volatility of wage changes rather than on wage levels.

	Movers			Stayers		
	Mean	S.D.	Median	Mean	S.D.	Median
ΔW_t	0.09	0.25	0.08	0.06	0.16	0.05
Age	31.92	10.74	30.00	34.62	11.47	34.00
Exp.	4.13	5.24	1.00	4.50	5.78	1.00
W_t	6.30	0.56	6.34	6.39	0.46	6.38
N	.023M			.7M		

Table 19: Summary statistics (selection)

6.3.5 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 paid 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 21).

	(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 20: Effect trimming wage change distribution on U-shape pattern

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 21 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 21: Effect time horizon on U-shape pattern

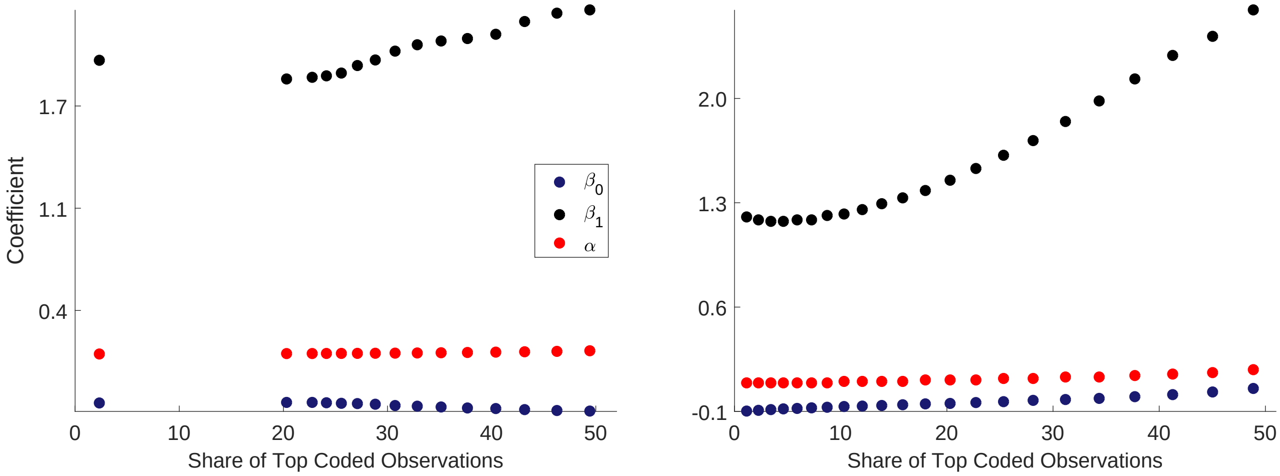
6.3.6 Censoring

Right censoring of the wage information in the Austrian and German[29] 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˙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

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

Figure 16b and 16a 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, Ludsteck, and Schönberg (2009)), I consider an observation as censored if it is 1.5 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 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.

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



(a) Germany

(b) Austria

Figure 16: Effect of Censoring on regression estimates

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

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 $\hat{\sigma}_j$.[30] Firm averages and volatilities computed for less than ten workers were excluded from the analysis.

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

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 22. 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. Note further that I do find some evidence of movements to lower quality firms for Austria. These results are not reported for Germany 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.

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

	Italy	Austria
1st Quintile ΔW_{t-1}	-0.019***	-0.015***
	(0.0030)	(0.0022)
2nd Quintile ΔW_{t-1}	-0.0069	-0.017***
	(0.0031)	(0.0023)
4th Quintile ΔW_{t-1}	-0.00064	-0.011***
	(0.0031)	(0.0023)
5th Quintile ΔW_{t-1}	0.0032	0.0038
	(0.0029)	(0.0022)
Cons.	0.056***	0.014***
	(0.0022)	(0.0017)
Observations	60K	160K

Standard errors in parentheses

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

Entries are in percentage differences from sending firm

Table 22: Change firm characteristics for movers

6.5 Analysis with US data

To address potential concerns about external validity beyond the European context, I take advantage of the US data set NLSY79. In addition to addressing external validity, the richness of the data and its survey design lend itself to consider the role of uncertainty and labor market experience more directly.[31] First, due to its construction with a focus on the young population, labor market experience is very well measured in this data set. Second, it contains information on personality characteristics that allow to consider the role of uncertainty more directly. For instance, Roca, Ottaviano, and Puga (2014) uses the Rosenberg measure of self-confidence in the NLSY79 to proxy for skill uncertainty. Finally, as the survey features information on risk preferences, I can also directly test whether differences in risk aversion across workers can account for the U-shape pattern.

First, figure 17 shows the main specification for the NLSY79. The U-shaped pattern is also visible within this sample. Each dot represents on average 2K workers. Second, table 23 shows the baseline specification in the linear probability model. Strikingly, the experience effect as shown in column (3) is stronger in this data set, such that on average workers with 15 years of labor market experience have no significant U-shape effect. More importantly, the data set allows to test for the effect of uncertainty about skills on separations. To do this, I use the fact that interviewees are ranked on the Rosenberg scale first in 1979 and second in 1987. The scale ranges from 10 to 40 points with high values indicating confidence (cf.

[31]Yet, this data set does not allow to test for coworker and firm effects as possible in the European matched data sets.

Roca, Ottaviano, and Puga (2014) for more details). In addition, interviewees are ranked on their ability. I therefore construct skill uncertainty as the absolute deviation between the standardized Rosenberg score and the ability score. I then use an instrumental variable approach to estimate the effect of skill uncertainty on separations.[32] As expected, the U-shape effect is strongest for those workers with low certainty about their ability, in line with the argument suggested in this paper. Moreover, the effect of experience drops after including skill uncertainty. Finally, the impact of skill uncertainty is independent of the actual skill level as measured through the AFQT score. This is mirrored in column (4) where the impact of uncertainty is quantitatively the same even after controlling for observed skills. Finally, in column (5) I further control for risk attitudes[33]. Risk attitudes do not seem to imply a strong impact on the U-shape pattern after controlling for experience and self-confidence. These conclusions are robust to controlling for both risk and skill levels, as done in column (6).

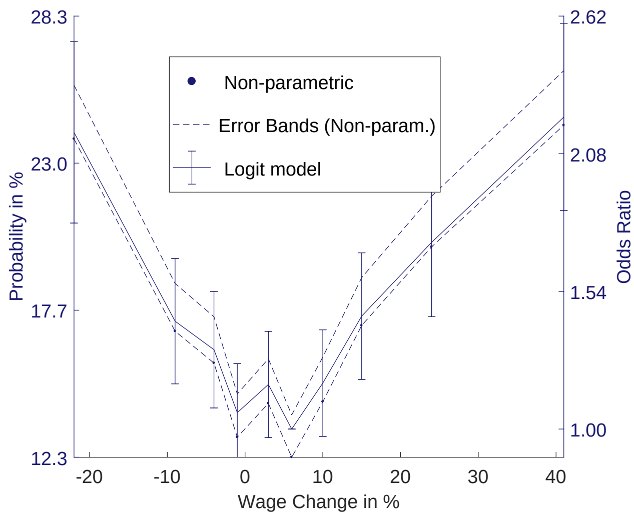


Figure 17: U-shape relation between wage growth and separation propensity (US)

[32]Specifically, I instrument for the most recent skill uncertainty with the 1979 score. I then use the predicted value in the standard linear probability model. I bootstrap the two-stage least squares design 100 times for standard errors.

[33]The question asks "Would you take a job that could either double the family income or cut your family income by a third? Would you take that job?" With answers as yes or no.

Table 23: U-shape pattern and uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta W_{i,j,t-1}$	-0.112***	-0.195***	-0.0986	-0.1100	-0.1175	-0.1226
	(0.0264)	(0.0532)	(0.1313)	(0.1395)	(0.1470)	(0.1459)
$(\Delta W_{i,j,t-1})^2$	1.961***	1.466***	2.524***	2.570***	2.509***	2.490***
	(0.0739)	(0.152)	(0.433)	(0.443)	(0.473)	(0.476)
$\Delta W_{i,j,t-1}$ X Exp. $_{i,j,t-1}$		0.0081	0.0128	0.0145	0.0181	0.0176
		(0.00696)	(0.0074)	(0.00907)	(0.0094)	(0.0095)
$(\Delta W_{i,j,t-1})^2$ X Exp. $_{i,j,t-1}$		-0.0931***	-0.0575*	-0.0716**	-0.0635*	-0.0637*
		(0.0206)	(0.0228)	(0.0252)	(0.0265)	(0.0263)
Exp. $_{i,jt-1}$		-0.00221***	-0.0042***	-0.0048***	-0.0046***	-0.0045***
			(0.00104)	(0.00114)	(0.00115)	(0.00115)
$\lvert A_{i,j,x} - a_i \rvert$			0.225***	0.224***	0.207***	0.209***
			(0.0214)	(0.0215)	(0.0137)	(0.0211)
$\lvert A_{i,j,x} - a_i \rvert$ X $(\Delta W_{i,j,t-1})^2$			-1.653***	-1.558***	-1.528***	-1.534***
			(0.455)	(0.470)	(0.4759)	(0.494)
$\lvert A_{i,j,x} - a_i \rvert$ X $\Delta W_{i,j,t-1}$			-0.1081	-0.1449	-0.0844	-0.0951
			(0.1354)	(0.1372)	(0.1424)	(0.142)
Observations	13K	13K	12K	11K	11K	11K

SE in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All except (1) control for $W_{i,j,t-1}$, (4)-(5) include interactions of $\Delta W_{i,j,t-1}$
and $(\Delta W_{i,j,t-1})^2$ with AFQT (4), risk attitudes (5) and both (6) respectively. SEs in (3)-(6) are bootstrapped.

6.6 Surplus Function

In the following, I report the surplus functions for the model with renegotiation of the surplus share. Let $V(J, I, O, M)$ 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 $V(J, I, 0, M^0) - U(I) = \alpha S(J, I, M^0)$. If workers match with a firm J' during on-the-job-search, they can leave their current firm J to receive $V(J', I, J, M^0) - U(I) = S(J, I, M^0) + \alpha(S(J', I, M^0) - S(J, I, M^0))$ 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: $V(J, I, J', M) - U(I) = S(J', I, M^0) + \alpha(S(J, I, M) - S(J', I, M^0))$. 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 $0 < V(J,I,O,M) - U(I) < S(J,I,M)$. I assume that the worker gets all the surplus ($V(J,I,O,M) - U(I) = S(J,I,M)$) whenever his incentive constraint is violated (if $V(J,I,O,M) - U(I) > S(J,I,M)$) and reversely for the firm $V(J,I,O,M) - U(I) = 0$ if $V(J,I,O,M) - U(I) < 0$. 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.

$$\begin{aligned}
V(J,I,O,M) &= \max\Bigg\{0, w + \beta\delta U(I) \\
&+ \beta(1-\delta)\Bigg[\lambda_1\Bigg(\int_{\mathcal{M}_2}\int_{\mathcal{M}_1} V(J',I',J,M^0)dF(J')dG^J(I') \\
&+ \int_{\mathcal{M}_2}\int_{\mathcal{M}_3} V(J,I',J',M')dF(J')dG^J(I')\Bigg) + \int_{\mathcal{M}_2}\Bigg(1-\lambda_1\int_{\mathcal{M}_{1/3}} dF(J')\Bigg) \\
&\quad \min\{V(J,I',O,M'), S(J,I',M') + U(I')\}dG^J(I') \\
&+ \int\Bigg(1 - \int_{\mathcal{M}_2} dG^J(I')\Bigg) U(I')dG^J(I')\Bigg]\Bigg\}
\end{aligned}$$

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

$$\begin{aligned}
V(\cdot) - U(I) &= \max\Bigg\{0, w - z - \beta\lambda^0\alpha\int_{\mathcal{M}_1} S(J',I,M^0)dF(J') + \beta\int U(I') - U(I)dG^J(I') \\
&+ \beta(1-\delta)\Bigg(\lambda_1\Bigg(\int_{\mathcal{M}_2}\int_{\mathcal{M}_1} V(J',I',J,M^0) - U(I')dF(J')dG^J(I') \\
&+ \int_{\mathcal{M}_2}\int_{\mathcal{M}_3} V(J,I',J',M') - U(I')dF(J')dG^J(I') \\
&+ \int_{\mathcal{M}_2}\Bigg(1-\lambda_1\int_{\mathcal{M}_{1/3}} dF(J')\Bigg) S_S dG^J(I')\Bigg)\Bigg\}
\end{aligned}$$

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

$$\begin{aligned}
P(J, I, O, M) &= \max\Bigg\{0, E[y_{i,j,t}] - w + \beta(1-\delta)\Bigg[\lambda_1 \int_{\mathcal{M}_2} \int_{\mathcal{M}_3} P(J, I', J', M') dF(J') dG^J(I') \\
&+ \int_{\mathcal{M}_2} \left(1 - \lambda_1 \int_{\mathcal{M}_{1/3}} dF(J')\right) P(J, I', O, M') dG^J(I')\Bigg]\Bigg\}
\end{aligned}$$

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

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

Using the contract rule, together with the equation for the surplus of the match to the worker, we obtain for wages$W(J, I, O, M)$

$$\begin{aligned}
W(J, I, O, M) &= SS(J, I, O, M) + z - \beta \int U(I') - U(I) dG^J(I') \\
&- \beta(1-\delta)\Bigg(\lambda^1\Bigg(\int_{\mathcal{M}_2} \int_{\mathcal{M}_1} SS(J', I', J, M^0) dF(J') dG^J(I') \\
&+ \int_{\mathcal{M}_2} \int_{\mathcal{M}_3} SS(J, I, J', M') dF(J') dG^J(I')\Bigg) \\
&+ \int_{\mathcal{M}_2} \left(1 - \lambda_1 \int_{\mathcal{M}_1 \cup \mathcal{M}_3} dF(J')\right) \mathrm{SS}_y dG^J(I')\Bigg) \\
&+ \beta\lambda^0\alpha \int_{\mathcal{M}_1} S(J', I, M^0) dF(J')
\end{aligned}$$

where $\mathcal{M}_1 : \{S(J', I', M^0) > S(J, I', M')\}$
$\mathcal{M}_2 : \{S(J, I', M') > 0\}$
$\mathcal{M}_3 : \{S(O, I', M^0) < S(J', I', M^0) < S(J, I', M')\}$
$SS(J, I, O, M) = S(O, I, M^0) + \alpha(S(J, I, M) - S(O, I, M^0))$
$\mathrm{SS}_y = \max\{0, \min\{SS(J, I', O, M'), S(J, I', M')\}\}$

6.7 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 $\beta_{i,t|t} = [N_{i,jt} \quad A_{i,t}]'$ 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)

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

$$\text{where} \quad \begin{array}{ll} X = [1 \quad \mu_j] & S_{yy} = J_h \Omega_{t|t-1} J_h' \\ \Psi = \text{diag}([\rho \quad 1]) & \Phi = \text{diag}([\sigma_j^2 \quad 0]) \\ \beta_t = [N_\tau \quad A_t]' & E[\widetilde{\beta}_{t-1}] \sim N(\beta_{t-1}, \Omega_{t-1}) \end{array}$$

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

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

$$\text{where} \quad \begin{array}{ll} \Psi = \text{diag}([\rho \quad 1]) & s = \sigma_{a,t-1}^2 (1 - I_{OTJ}\rho)^2 / \sigma_j^2 \\ \Omega = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} & \xi_t = y_t - v(\mu_j, A_t) - \rho N_{i,j,t} \end{array}$$

6.8 Variance of Changes in Beliefs

In the following, I derive the formula for the variance of changes in beliefs $A_{i,t}$ for two cases; for $\rho = 0$ and $\rho > 0$.

6.8.1 Absence Autocorrelated Productivity Shocks

First, note that

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

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

$$A_{t-1} = \beta_{t-2}\left(\frac{A_0}{s_0} + a_i(t-1) + \sum_{k=1}^{t-1}\epsilon_k\right)$$

From this formulation, it is not directly obvious that A_t converges to its true value a_i. This however becomes clear when noting that the precision of the belief $\phi_{a,t} = 1/\sigma_{a,t}$ evolves linearly in time as $\phi_{a,t} = \phi_{a,0} + t\phi_j$ where $\phi_j = 1/\sigma^2$. Hence, $s = 1/(\frac{\phi_{a,0}}{\phi_j} + t) = s_0/(1+ts_0)$ such that $\beta_{t-1} = \frac{s_{t-1}}{1+s_{t-1}} = \frac{s_0}{1+s_0 t}$. As a result, $\beta_{t-2}a_i(t-1)$ indeed converges to a_i.
The formula for the variance of changes in A_t is then

$$\mathrm{Var}\left(\Delta A_t\right) = \beta_{t-1}^2\left(\mathrm{Var}(a_i)(1-\beta_{t-2}(t-1))^2 + \sigma^2\left(1 + \beta_{t-2}^2((t-1)+1/s_0)\right)\right)$$

where $\beta_{t-1} = \frac{s_0}{1+s_0 t}$ and $\beta_{t-2} = \frac{s_0}{1+s_0(t-1)}$. The variance of ΔA_t is a function of $\sigma_{a,0}, \sigma^2$, $\mathrm{Var}(a_i)$ and experience t. Given the definition of $\beta_{t-2} = \frac{s_0}{1+s_0(t-1)}$, it is straight forward to see that $\mathrm{Var}\left(\Delta A_t\right)$ is converging to zero with experience.

6.8.2 Presence Autocorrelated Productivity Shocks

When workers learn also about match specific productivity,

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

where $\beta_{t-1} = \frac{s_{t-1}}{(1+s_{t-1})(1-I_{OTJ}\rho)}$ and $s_{t-1} = \sigma^2_{a,t-1}(1 - I_{OTJ}\rho)^2/\sigma^2$. In this case,

$$A_{t-1} = \tilde{\beta}_{t-2}\left(\frac{A_0}{s_0} + a_i(t-1) + \sum_{k=1}^{t-1}\frac{\epsilon_k}{(1 - I_{OTJ}\rho)}\right)$$

where $\tilde{\beta}_{t-1} = \beta_{t-1}(1 - I_{ITJ}\rho)$. The variance of changes in beliefs is therefore

$$\text{Var}\,(\Delta A_t) = \tilde{\beta}^2_{t-1}\left(\text{Var}(a_i)(1 - \tilde{\beta}_{t-2}(t-1))^2 + \frac{\sigma^2}{(1-\rho)}\left(1 + \tilde{\beta}^2_{t-2}((t-1) + (1-\rho)/s_0)\right)\right)$$

where $\beta_{t-1} = \frac{s_0}{1+s_0 t}$ and $\beta_{t-2} = \frac{s_0}{1+s_0(t-2)}$. The variance of ΔA_t is a function of $\sigma_{a,0}, \sigma^2$,$\text{Var}(a_i)$, ρ, t and is converging to zero with experience t for $\rho < 1$.

In this case, the variance of changes in expected output, equal to productivity, is a more relevant characteristic as it equals the variance of wage changes in the case of $\alpha = 1$. In this case,

$$\text{Var}(\Delta W_t) = (1-\rho)^2\text{Var}(\Delta A_{t-1}) + \rho^2\text{Var}(\Delta n_{t-1})$$

As a result, the variance of wage changes in this case is decreasing up to $\rho^2\text{Var}(\Delta n_{t-1}) > 0$.

6.9 Dynamic Match Productivity and Wages

In the following, assume that workers reap the whole surplus of the match. In this case, wages equal expected output $W_t = E[y_{i,j,t}] = A_{t-1} + \mu_j + \rho N_{t-1}$ such that

$$\begin{aligned}\Delta W_t &= \Delta A_{t-1} + \rho \Delta N_{t-1} \\ &= \Delta n_{t-1} - (1-\rho)\Delta N_{t-1} \\ &= \rho \Delta n_{t-1} + (1-\rho)\Delta A_{t-1}\end{aligned}$$

for all levels of tenure higher than or equal to 1. To see that the last two line holds, note that (given $\xi_{t-1} = y_{i,j,t-1} - E[y_{i,j,t-1}] = (a_i - A_{t-2}) + \rho(n_{t-2} - N_{t-2}) + \epsilon_{t-1}$)

$$\begin{aligned}\Delta A_{t-1} + \Delta N_{t-1} &= \beta_{t-2}^2 \xi_{t-1} + (\rho - 1)N_{t-2} + (1 - \beta_{t-2}^2)\xi_{t-1} \\ &= (\rho - 1)N_{t-2} + \xi_{t-1} \\ &= (a_i - A_{t-2}) + (n_{t-1} - N_{t-2}) = \Delta n_{t-1}\end{aligned}$$

The before last line uses the updating equations,

$$\begin{aligned}A_{t-1} &= \beta_{t-2}^2 A_{t-2} + (1 - \beta_{t-2}^2)(a_i - \rho N_{t-2} + n_{t-1}) \\ N_{t-1} &= (1 - \beta_{t-2}^2)\rho N_{t-2} + \beta_{t-2}^2(a_i - A_{t-2} + n_{t-1}) \\ &= -A_{t-1} + (a_i + n_{t-1})\end{aligned}$$

which holds for all levels of tenure higher than or equal to 1.

6.10 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, Fitzenberger, Schönberg, and Spitz-Oener (2014), Addison, Teixeira, Stephani, and Bellmann (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, Fitzenberger, Schönberg, and Spitz-Oener (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 memebership 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 agreements 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, Kraeussl, and Monticone

(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 representatives, 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, Stahl, Winter-Ebmer, and Zweimüller (2003)), giving witness of a relatively flexible labor market despite regulations.

6.11 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 endogeneous 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 endogeneous 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 nor does a hightened variance of wage changes indicate a low level of human capital.

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 focus on the duration of non-employment after displacement. 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. I assume that workers with higher human capital stocks have lower non-employment durations upon separation.

Hence, I consider the mean duration of non-employment after a displacement as a function of the last observed wage change in the previous job. I use a linear probability model 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. As table 24 shows, I I find however that there is a no evidence for a U-shape relation in the duration of observed non-employment for agents that had high or low wage changes during the previous work spell for Italy and Austria.

	Italy	Austria
ΔW_{t-1}	-2.18***	-1.18***
	(0.28)	(0.22)
$(\Delta W_{t-1})^2$	0.87***	0.01***
	(0.15)	(0.09)
Constant	1.47***	7.66***
	(0.034)	(0.031)
N	87K	214K

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

Table 24: Duration non-employment after displacement

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