Essays in Macro-Labor

Agnieszka Dorn

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ABSTRACT

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In the first chapter of this dissertation, I estimate the cyclicality of real wages for job stayers, and hires from both employment and from unemployment, using an administrative matched employer-employee dataset from Germany. I find that the wages of new hires appear to be less procyclical than the wages of job stayers. The finding can be explained by countercyclical selection: when aggregate productivity is low, worker-firm matches have to be unusually productive to warrant job creation. The match productivity (quality) is not observed directly. However, the job duration serves as a proxy for match quality. I find that the relationship between the initial aggregate conditions and the subsequent risk of separation is negative: employment started when unemployment is higher is at a decreased risk of ending with a separation to unemployment. This finding indicates that match quality is countercyclically selected, rising during economic downturns.

Motivated by the empirical findings of the first chapter, I show that countercyclical selection over match quality arises naturally in a Diamond-Mortensen-Pissarides search and matching model with two key components: match-specific productivity and turnover costs. In the model, match-specific productivity undergoes countercyclical selection: when aggregate productivity is low, match-specific productivity has to high to justify creating or maintaining a match. Due to turnover costs, countercyclical selection for new hires is stronger than for job stayers. The relative cyclical properties of wages are induced by changes in average match-specific productivity for new hires relative to job stayers. Lower match-specific productivity of matches started when aggregate productivity is high leads to higher risk of subsequent separation. I calibrate the model using external sources. Crucially, observed wage dispersion and hiring costs inform the match-specific productivity distribution and a hiring cost parameter. The model-generated wages and job durations have cyclical properties empirically established in the previous chapter: the wages of new hires are less procyclical than the wages of job stayers, and jobs started when productivity is

higher are at a higher risk of subsequent separation.

In the third chapter, I examine the behavior of wages within employment spells, before separations from a job and after transitions between jobs. Using German administrative microdata, I establish three empirical findings. First, the properties of wage changes within employment spells and associated with job-to-job transitions are broadly similar and follow the same patterns across demographic groups and time. In particular, the fraction of job-to-job transitions associated with wage cuts, 31%, is not drastically higher than the fraction of wage cuts in all wage changes within employment spells, 26%. Second, wages deteriorate in the year preceding separation from a job, for all separations, including job-to-job transitions. The wage deterioration manifests both as slower wage growth and as lowering of real wages expected given workers' characteristics. Third, for job-to-job transitions wage growth after accession is faster if the initial wage is lower than the last wage in the previous job. This effect is not present for job-unemployment-job transitions. The second finding supports the notion that some job-to-job transitions happen because of the worsened job situation. However, the third finding suggests that, to some extent, workers might voluntarily make job-to-job transition that decreases their wages in expectation of higher wage growth in the future.

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Chapter 1

The Cyclicality of Wages and Match Quality: Empirical Evidence from German Microdata

1.1 Introduction

Unemployment is volatile relative to aggregate shocks, as discussed in Shimer (2005) and Pissarides (2009). Changes in incentives for job creation are an important driver of unemployment, since it is driven more by fluctuations in job creation and job finding than by fluctuations in separations.[1] The incentives for job creation depend on the expected cost of labor, which is proxied by the wages of new hires. Consequently, the cyclical behavior of wages is crucial for understanding the cyclical behavior of unemployment.

To investigate the cyclicality of wages, I estimate the relationship between the real wages and the unemployment rate using a matched employer-employee administrative dataset from Germany. The dataset allows for differentiating between two types of hires,[2] from employment and unem-

[1]See Hall (2005) or Shimer (2012) for a discussion of the decomposition of unemployment fluctuations.

[2]The differentiation between hires from employment and unemployment has been neglected in the wage cyclicality literature until recently. Notable recent exceptions are Getler, Huckfeldt and Trigari (2016) who find that the wages

ployment,[3] and addressing the potential biases: due to worker heterogeneity, as discussed in Bils (1985) and Solon, Barsky and Parker (1994); due to occupational down- or upgrading; and due to the differences between cyclicality of employment at high- and low-paying firms.[4]

Contrary to expectations, the wages of new hires are *less* procyclical than the wages of job stayers. This effect is stronger for hires from employment than for hires from unemployment. This counterintuitive result requires an explanation.

I propose an explanation based on countercyclical changes in the quality of firm-worker matches. Aggregate productivity has a direct effect on wages, as well as an indirect effect due to selection on match quality that acts in the opposite direction to the direct effect. During downturns, worker-firm pairs have to be unusually productive to warrant job creation. The average match quality for new hires is higher than for job stayers. Low aggregate productivity has a direct, negative effect on wages, as well as an indirect positive effect on the wages of new hires. In contrast, the opposite happens during upturns, as even low-quality matches are productive enough to be created. High aggregate productivity has a direct, positive effect on wages, as well as an indirect negative effect on the wages of new hires.

The presence of the match quality selection effect is empirically validated. As observed in Bowlus (1995), matches of better quality, which I conceptualize as match-specific productivity, should last longer. I investigate the relationship between risk of separation to unemployment, a proxy for match quality, and the unemployment rate at the start of a job. The relationship is nega-

of hires from employment are more procyclical and the wages of hires from unemployment are no more cyclical than those of job stayers, and Haefke, Sonntag, and van Rens (2013), who find that changes in the wages of hires from unemployment closely follow aggregate labor productivity.

[3]Throughout the paper, ”unemployment” refers to both unemployment and non-employment.

[4]Recently, Moscarini and Postel-Vinay (2012), Kahn and McEntarfer (2014), and Haltiwanger, Hyatt and McEntarfer (2015) investigated the cyclical properties of employment and employment growth for different categories of firms. Their findings raise the possibility that lower-paying firms are responsible for a higher share of employment and hires during downturns, which would introduce procyclical bias into the estimates of wage cyclicality.

tive: higher unemployment at the start of a job is associated with a decreased risk of a job ending with a separation to unemployment. This association is stronger for hires from employment than for hires from unemployment. These results support my hypothesis that matches started during downturns are positively selected, especially when they are created by a job-to-job transition.

1.2 Related Literature

In this section, I discuss how the results of this paper relate to the literature on the cyclical properties of real wages and the previous findings on the separation risk as a proxy for match quality.

1.2.1 Cyclicality of Wages

How do real wages react to business cycle conditions? At least since the Dunlop-Tarshis-Keynes exchange, this simple question has been the subject of a large body of research and is still not fully answered. In recent years, the interest in this issue was renewed after Shimer (2005) argued that the Diamond-Mortensen-Pissarides search and matching model had difficulty reconciling fluctuations in unemployment and fluctuations in productivity. As emphasized in Pissarides (2009), establishing how real wages behave over the business cycle is crucial for understanding cyclical fluctuations in unemployment. This paper belongs to a recent wave of papers that use microdata to investigate the cyclicality of wages.

Up to the early 1990s, the consensus, based on studies using aggregate data, was that real wages in the US were acyclical or, at best, weakly procyclical. These studies were suspected to suffer from various forms of composition bias. As Stockman (1983) surmised, the composition of the labor force changes over the business cycle: hours and employment of low-wage workers are more procyclical than hours and employment of all workers, which induces a countercyclical bias in an aggregate measure of wages. An opposite procyclical bias was identified in Chirinko (1980) as arising from high cyclical sensitivity of high-wage industries such as durables manufacturing and construction.

The use of individual level data shattered the previous consensus, starting with Bils (1985) and Solon, Barsky and Parker (1994). Wages were usually found to be procyclical.

Newer papers differentiate not only between job stayers and new hires but also hires from unemployment and employment. A recent example is Haefke, Sonntag and van Rens (2013), which uses CPS cross-sectional data and finds that the elasticity of wages with respect to labor productivity is higher for hires from unemployment than for job stayers, and even higher for hires from employment, although the standard errors are large. A different conclusion is reached in Gertler, Huckfeldt and Trigari (2016), which uses SIPP panel data and to finds that the wages of job stayers are slightly procyclical, the wages of hires from unemployment are acyclical and the wages of hires from employment are procyclical.

Studies of the US labor market suffer from data limitations. Suitable datasets are, at best, panels. They contain scanty information on employers and often unsatisfactory information on workers. Wages, earnings and hours are plagued by measurement error. The use of administrative datasets reduces measurement error issues and allows to control for various potential sources of composition bias. Recent examples are Carneiro, Guimaraes and Portugal (2012) and Martins, Solon and Thomas (2012), which use Portuguese Quadros de Pessoal, a matched employer-employee dataset. In the first paper, the cyclicality of wages is estimated with controls for worker, job and occupation fixed effects. The wages of new hires are found to be more procyclical than the wages of job stayers. The second paper concentrates on hiring wages for a set of entry jobs, which are found to be quite procyclical. Due to limitations of the dataset, these papers cannot differentiate between hires from employment and those from unemployment.

For Germany, Stueber (2017) used a similar source of data as my paper, the employment biographies generated by the German social security system, but considered the period 1977-2009 at a yearly frequency. The wages of new hires were found to be no more procyclical, when controlling for worker and employer-occupation fixed effects, than the wages of job stayers.

1.2.2 Match Quality

Is match quality higher or lower in jobs started in periods of high unemployment than those started in periods of low unemployment? Match quality, however defined, is not directly observable. Bowlus (1995) introduced the idea that job duration can serve as a proxy for its quality - better matches should last longer. Using job duration until transition to different employment or unemployment as a proxy for match quality is equivalent to investigating the instantaneous probability of separation conditional on previous survival (the hazard rate). Consequently, the relationship between the conditions at the start of a job and the subsequent risk of separation carries information about the cyclical properties of the match quality for new hires.

Bowlus (1995), the first to use job duration as a proxy for match quality, found that a higher initial unemployment rate increased the subsequent risk of separation. This finding, suggestive of procyclical match quality, motivated Barlevy (2002) to formulate a theory of sullying recessions. Baydur and Mukoyama (2018) used the competing risks model, finding that a higher initial unemployment rate increased the risk of job-to-job transition but decreased the risk of separation into nonemployment.

These papers used panel data from the National Longitudinal Survey of Youth, which precluded controlling for firm heterogeneity. Kahn (2008) exploited a small matched dataset of Fortune 500 firms and their employees. Controlling for firm heterogeneity switched the sign of the relationship between the separation risk and the initial unemployment rate from positive to negative. I observe a similar phenomenon - controlling for firm heterogeneity plays a crucial role in the analysis of the relationship between the conditions at the start of a job and the subsequent risk of separation. My findings, together with Kahn (2008), indicate that the average match quality for new hires might be countercyclical in the US as well as in Germany, contrary to most of previous findings. To the best of my knowledge, this paper is the first to conduct such an analysis controlling for firm heterogeneity and using a large matched sample of firm and workers.

1.3 Data

I use a German matched employer-employee dataset data provided by the Research Data Centre of the Federal Employment Agency at the Institute for Employment Research (IAB). The Linked Employer-Employee Data Longitudinal Model 1993-2010 (LIAB LM 9310) contains administrative data on all workers that were employed at any time between 1999 and 2009 in one of the establishments covered by the 2000-2008 panel of the IAB Establishment Panel. The sample of establishments is drawn from the population of all establishments with employees subject to social security and stratified with respect to industry, size and federal state. A detailed description is provided in Klosterhuber, Heining and Seth (2014).

For each worker, I have information on all employment spells subject to social security between 1993 and 2010: an establishment identifier; sex; education; working hours (full-time or part-time); employment status (indicators for special status such as traineeship, partial retirement and others); daily earnings; occupation, with 120 occupational categories; and other information. Job tenure can be precisely calculated.

The dataset lacks precise information on working hours, but I observe whether a worker works full-time or part-time. Workers are classified as full-time if their contracted hours are the usual working hours in the establishment. Consequently, when I restrict the sample to full-time workers, the firm fixed effects control for differences in working hours across establishments.

The observations with daily earnings above the legally mandated contribution assessment ceiling (Beitragsbemessungsgrenze) are topcoded. More than 10% of the observations are affected. Using the Tobit regression with the same control variables as for the censored sample is computationally infeasible. Instead, to establish that it is implausible that my results are affected by censoring, I use a robustness check the replaces worker and firm fixed effects with the CHK estimates from Card, Heining, Kline (2013). They estimated a Mincer-type wage model with additive fixed effects for workers and establishments for all West German workers covered by social security. The estimated worker fixed effects represent a component of a wage that a worker receives wherever he works, controlling for his observable characteristics. The estimated firm fixed effects represent a wage component common to all workers in a firm, controlling for their observable and unobservable characteristics. The IAB provided a supplementary dataset with the CHK estimates.

The main sample is restricted to the spells of employment in West German establishments that are the 2000-2008 panel cases of the IAB Establishment Panel. I restrict the sample to men aged 20-60. This restriction is adopted for comparability with earlier studies.

1.4 Empirical Results

This section presents the specification and the results for the estimation of the cyclicality of wages, and for the estimation of the relationship between the risk of separation and the initial conditions.

1.4.1 Wages: Specification

The specification for estimating the cyclicality of wages follows Gertler, Huckfeldt and Trigari (2016). Data are at a monthly frequency. Let w_{it} denote the real wage paid in period t to individual i. The wage equation is

$$log\, w_{it} = \pi u_t + \pi_E NH_E(i,t)u_t + \pi_U NH_U(i,t)u_t + \alpha_i + \beta_{j(i)} + \boldsymbol{\gamma}_x' \boldsymbol{x}_{it} + \epsilon_{it} \tag{1.1}$$

where u_t is the unemployment rate, $NH_E(i,t)$ and $NH_U(i,t)$ are indicator variables that take value one for new hires from employment and from unemployment, respectively. The controls are worker fixed effects α_i, firm fixed effects $\beta_{j(i)}$, where $j(i)$ denotes i's employer, and additional variables contained in vector $\boldsymbol{x}_{it}$: indicators for both types of new hires; a time trend (calendar-month dummies and a quadratic polynomial in time); an education-specific cubic polynomial in age; a cubic polynomial in tenure when applicable; and occupation fixed effects.

Hires from employment are identified as workers that started their current job no more than 14 days after the end of their previous employment and without registering as an unemployed or a jobseeker. Hires from unemployment are identified as workers that started their current job more than 14 days after the end of their previous employment or after registering as an unemployed or a jobseeker. The results are robust to changing the cutoff for differentiation between hires from employment and unemployment to 31 days and to 7 days.

In Table 1.1, I present the estimates of the wage cyclicality for few variants of specification (1.1). The results for the full specification are in column (7). Columns (1)-(6) show results for specifications without some of the control variables. The results from the Tobit regression that uses an uncensored sample, with the CHK effects replacing worker and firm fixed effects, are shown in column 5 of Table 1.3. Columns (1)-(4) show results for variants of specification (1.1) used for comparisons with the Tobit regression. The estimates for a sample that includes part-time workers are shown in column 6 of 1.3.

The coefficients of interest are π, the semielasticity of wages with respect to the unemployment rate u_t, and the incremental effects for hires from employment and from unemployment, π_E and π_U. The cyclicality of wages is captured by π, $\pi + \pi_E$, and $\pi + \pi_U$ for job stayers, new hires from unemployment and employment, respectively.

1.4.2 Wages: Results

The results in the first four columns on Table 1.1 show the estimates of π, π_E, and π_U for the specifications that sequentially add more controls for worker heterogeneity: observable workers' characteristics in column (2), worker fixed effects in column (3), and occupation fixed effects in column (4). The estimates of wage cyclicality decrease substantially when controls are added. An exception are occupation fixed effects, which addition leaves the estimates essentially unchanged.

These results are consistent with both job stayers and new hires having better observable and unobservable characteristics when unemployment is higher. Cyclical occupational up- or downgrading seems to have negligible effects.

The addition of firm fixed effects lowers the estimates in comparison with the specification without any controls, as the comparison of columns (5) and (1) reveals. By themselves, these results suggest countercyclical changes in the quality of firms that retain and hire workers, although the firm fixed effects are difficult to interpret on their own since they might pick up differences in workforce characteristics or differences in usuak working hours across firms.

The estimates from the specifications without and with firm fixed effects in addition to full worker controls, presented in columns (3)-(4) and (6)-(7), reveal that the addition of firm fixed effects is unimportant for the wage cyclicality of job stayers but lowers the cyclicality of wages for new hires, in particular hires from unemployment, which suggests countercyclical changes in the

Table 1.1: Wage Cyclicality Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\pi}$	0.634^{***}	0.350^{***}	-0.097^{**}	-0.091^{**}	0.392^{***}	-0.097^{**}	-0.091^{**}
	(0.058)	(0.057)	(0.042)	(0.041)	(0.052)	(0.042)	(0.042)
$\hat{\pi}_E$	1.543^{**}	1.598^{**}	0.769^{***}	0.773^{***}	1.553^{***}	0.706^{***}	0.718^{***}
	(0.671)	(0.737)	(0.223)	(0.238)	(0.379)	(0.161)	(0.178)
$\hat{\pi}_U$	3.167^{***}	2.783^{**}	0.410^{**}	0.450^{**}	1.086^{**}	0.338^{**}	0.384^{**}
	(1.149)	(1.086)	(0.201)	(0.201)	(0.500)	(0.169)	(0.172)
adj. R-sq	0.014	0.227	0.866	0.866	0.396	0.867	0.867
N	24751079	24751079	24736866	24663419	24751073	24736866	24663419
Firms	3434	3434	3427	3421	3428	3427	3421
Workers	443987	443987	429774	426886	443981	429774	426886
Worker Controls	No	Yes	Yes	Yes	No	Yes	Yes
Occupation FE	No	No	No	Yes	No	No	Yes
Worker FE	No	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes

Notes: * p< .1, ** p<.05, *** p<.01; time-clustered standard errors in parentheses; uncensored observations for full-time non-trainee workers.

quality of hiring firms.

The results for the full version of specification (1.1), shown in column (7) of Table 1.1, indicate that the wages of job stayers are procyclical. However, the wages of new hires are less procyclical than than the wages of job stayers, since the incremental effects π_E and π_U are estimated to be positive. This effect is more pronounced for hires from employment than from unemployment. Adding occupation fixed effects is again unimportant, as shown by the similarity of the results in columns (7) and (6) which are obtained for the specifications with and without occupation fixed effects, respectively.

The robustness check that estimates the wage cyclicality for the whole sample yields reassuring results, presented in Table 1.3. I compare the results of the Tobit estimation on the whole sample, column (5), to the analogous results in column (1) from the estimation that uses only the uncensored observations. Both specifications use the CHK estimates as controls for worker and firm heterogeneity. The estimated wage cyclicality is similar. In turn, the estimates in column (1) are similar to the estimates in column (2), with occupation fixed effects, and the estimates in columns (1) and (2) are similar to the fixed-effects results in columns (3) and (4).

I estimate the wage equation using a sample that includes part-time workers, adding fixed effects for working hours and employment status. The results in column 6 of Table 1.3 are, again, qualitatively similar to the main results.

1.4.3 Separation Risk: Specification

The risk of separation is captured by the hazard rate defined as the instantaneous probability that worker i experiences an event, in this case a separation, conditional on the event not happening up to time d from the start of exposure to risk, in this case hiring, and the information set summarized in vector $\boldsymbol{z}_{id}$:

$$h_{id} = lim_{\Delta d \to 0} \frac{P(d \leq D_{event} < d + \Delta d | D_{event} \geq d,\ \boldsymbol{z}_{id})}{\Delta d},$$

where D_{event} is a random variable, the time from the exposure start when the event happens.

I use the Cox (1972) model of the hazard rate, in which the hazard rate takes the functional form

$$h_{id} = \tilde{h}_{jd} exp(\boldsymbol{\beta'} \boldsymbol{z}_{id} + \epsilon_{id})$$

where β is a vector of parameters common for all observations, and $\tilde{h}_{jd}$ is the baseline hazard rate, which might differ across subsets (strata) of observations, in this case firms $j = j(i)$. For comparisons with previous papers, I estimate two versions of the Cox model: unstratified, in which the baseline hazard rate is the same for all firms, $\tilde{h}_{jd} = \tilde{h}_d$; and stratified, in which the baseline hazard rate $\tilde{h}_{jd}$ is allowed to vary across firms.

The stratified Cox model is a modification of the Cox proportional hazards model that allows the baseline hazard to differ across strata. Stratification in the Cox model is a counterpart of adding fixed effects to linear models. The strata in my estimation are firms, allowing for differences in the baseline hazard across firms.

The information set for worker i at time d, captured in a vector $\boldsymbol{z}_{id}$, includes the unemployment rate at the start of a job, $u_{ij}^{initial}$, the indicator for hires from unemployment, H_{ij}^U, the indicator interacted with the initial unemployment rate, a time trend, initial wage, current unemployment rate and its square and other controls for observable worker heterogeneity.

The main estimation equation is

$$h_{id} = \tilde{h}_{jd} exp(\alpha u_{ij}^{start} + \alpha_U H_{ij}^U u_{ij}^{start} + \boldsymbol{\gamma}_x' \boldsymbol{x}_{id} + \epsilon_{id}), \tag{1.2}$$

where $\boldsymbol{x}_{id}$ contains elements of $\boldsymbol{z}_{id}$ other than u_{ij}^{start} and $H_{ij}^U u_{ij}^{start}$.

For comparison with previous papers, I estimate the equation (1.2) in the stratified and unstratified version and pool together 2 types of hires, estimating

$$h_{id} = \tilde{h}_{jd} exp(\alpha u_{ij}^{start} + \boldsymbol{\gamma}_x' \boldsymbol{x}_{id} + \epsilon_{id}), \tag{1.3}$$

also in the stratified and unstratified version.

The results of the estimation of (1.2) with and without stratification across firms are in Tables 1.2 and 1.4, respectively. The results of the estimation of (1.3) with and without stratification across firms are in Tables 1.5 and 1.6. Columns (1) present the results for separations pooled together, columns (2) for separations to employment, columns (3) for separations to unemployment.

In specification (1.2), the coefficients of interest are α, which captures the relationship between the initial unemployment rate and the subsequent risk of separation for hires from employment, and the incremental effect α_U for hires from unemployment. For hires from unemployment, the relationship between the initial unemployment rate and the subsequent risk of separation is captured by $\alpha + \alpha_U$. In specification (1.3), the coefficient of interest is α.

1.4.4 Separation Risk: Results

The main results from the stratified Cox model with the incremental effect for hires from unemployment, presented in Table 1.2, suggest that a higher initial unemployment rate decreases the subsequent risk of separation to unemployment but not the risk of a job-to-job transition. This cyclical property is present, but attenuated, for hires from unemployment. When both types of separations are considered together, as in some previous papers, the relationship between the initial unemployment rate and the subsequent risk of separation is negative.

The unstratified Cox model yields different results, presented in Table 1.4. A higher initial unemployment rate decreases the subsequent risk of separation to employment. When both types of separations are considered together, the relationship between the initial unemployment rate and risk of separation is positive for hires from employment, although not significant for both types of hires considered together, as shown in column (1) of Table 1.6.

Controlling for firm heterogeneity has similar effects as in Kahn (2008), which used a small matched dataset with on large US firms and their employees. This raises a possibility that the estimates of the relationship between the initial unemployment rate and the subsequent risk of separation that neglect firm heterogeneity are biased.

Table 1.2: Estimates for Job Duration, Stratification

	All Separations	EE Separations	EU Separations
	(1)	(2)	(3)
$\hat{\alpha}$	-4.532^{***}	-0.211	-13.18^{***}
	(1.693)	(2.122)	(1.509)
$\hat{\alpha}_U$	0.412	2.366	5.037^{***}
	(1.031)	(1.556)	(1.093)
N	8465856	8465856	8465856
Firms	4137	4137	4137
Workers	269334	269334	269334

Notes: * p< .1, ** p<.05, *** p<.01; time-clustered standard errors in parentheses; stratification by establishment.

1.5 Conclusions

The relationship between the business cycle and real wages is one of the oldest topics in macroeconomics. I explored the previously neglected possibility that the cyclical changes in average match quality are reflected in the estimates of wage cyclicality. Using German administrative microdata, I found evidence of the presence of countercyclical selection on match quality for new hires. The estimates of both the wage cyclicality and the relationship between the initial conditions and the subsequent risk of separation support my hypothesis of the match quality selection effect. In the next chapter, I show that the match quality selection effect arises in a standard Diamond-Mortensen-Pissarides search and matching model with two key features: match-specific productivity and turnover costs.

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Appendix A: Wage Cyclicality

Table 1.3: Robustness of Wage Cyclicality

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\pi}$	-0.121^{***}	-0.123^{***}	-0.097^{**}	-0.091^{**}	-0.228^{***}	-0.018
	(0.043)	(0.043)	(0.042)	(0.042)	(0.042)	(0.044)
$\hat{\pi}_E$	0.922^{***}	0.911^{***}	0.706^{***}	0.718^{***}	0.916^{***}	0.718^{***}
	(0.250)	(0.242)	(0.161)	(0.178)	(0.215)	(0.160)
$\hat{\pi}_U$	0.389	0.544^{*}	0.338^{**}	0.384^{**}	0.306	0.121
	(0.327)	(0.305)	(0.169)	(0.172)	(0.291)	(0.121)
adj. R-sq	0.765	0.774	0.867	0.867	–	0.935
Firms	3434	3428	3427	3421	3439	3433
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes
Worker FE	No	No	Yes	Yes	No	Yes
Worker CHK	Yes	Yes	No	No	Yes	No
Firm FE	No	No	Yes	Yes	No	Yes
Firm CHK	Yes	Yes	No	No	Yes	No
Uncensored	Yes	Yes	Yes	Yes	No	Yes
Full-Time	Yes	Yes	Yes	Yes	Yes	No

Notes: * p< .1, ** p<.05, *** p<.01; time-clustered standard errors in parentheses.

Appendix B: Separation Risk

Table 1.4: Estimates for Job Duration, No Stratification

	All Separations (1)	EE Separations (2)	EU Separations (3)
$\hat{\alpha}$	4.170^{*}	11.91^{***}	-9.941^{***}
	(2.254)	(3.286)	(1.710)
$\hat{\alpha}_U$	-4.910^{**}	-5.862^{*}	4.389^{***}
	(2.111)	(3.032)	(1.658)
N	8465856	8465856	8465856
Firms	4137	4137	4137
Workers	269334	269334	269334

Notes: * p< .1, ** p<.05, *** p<.01; time-clustered standard errors in parentheses; stratification by establishment.

Table 1.5: Estimates for Job Duration, All Hires, Stratification

	All Separations	EE Separations	EU Separations
	(1)	(2)	(3)
$\hat{\alpha}$	-3.959^{***}	0.731	-9.044^{***}
	(1.397)	(1.726)	(1.270)
N	8465856	8465856	8465856
Firms	4137	4137	4137
Workers	269334	269334	269334

Notes: * p< .1, ** p<.05, *** p<.01; time-clustered standard errors in parentheses; stratification by establishment.

Table 1.6: Estimates for Job Duration, All Hires, No Stratification

	All Separations	EE Separations	EU Separations
	(1)	(2)	(3)
$\hat{\alpha}$	1.467	9.872^{***}	-7.623^{***}
	(1.528)	(2.435)	(1.424)
N	8465856	8465856	8465856
Firms	4137	4137	4137
Workers	269334	269334	269334

Notes: * p< .1, ** p<.05, *** p<.01; time-clustered standard errors in parentheses.

Chapter 2

The Cyclicality of Wages and Match Quality: A Theoretical Explanation

2.1 Introduction

In the previous chapter, I use matched employer-employee administrative microdata from Germany to establish two empirical facts: the wages of new hires are less procyclical than the wages of job stayers, and there is a negative relationship between the initial unemployment rate and the subsequent risk of separation. In this chapter, I show that these properties of wage cyclicality and job duration arise naturally in a Diamond-Mortensen-Pissarides search and matching model with match-specific productivity ("match quality") and turnover costs in the form of a hiring cost.[1]

I outline a mechanism that explains how the wages of new hires can be less procyclical than for job stayers due to the cyclical properties of the average match-specific productivity for two groups. The wages are determined by Nash bargaining over the match surplus, which depends on aggregate productivity and match-specific productivity. The average match-specific productivity moves in

[1]As discussed later, the presence of a firing cost has the same effect.

the opposite direction to aggregate productivity for both job stayers and new hires, which affects the wages countercyclically. The presence of turnover costs drives a wedge between the lowest viable match-specific productivity for new hires and job stayers, making changes in the average match-specific productivity more pronounced for new hires. As a result, the average match-specific productivity for new hires is countercyclical in both absolute terms and relative to job stayers, which dampens procyclicality of the wages of new hires relative to the wages of job stayers.

The presence of low productivity matches that can be created only when productivity is high drives a positive relationship between initial aggregate productivity and the subsequent risk of separation, which translates into the negative relationship between the initial unemployment rate and the separation risk. The low productivity matches undergo an endogenous separation when aggregate productivity drops.

When aggregate productivity is high, even matches with low match-specific productivity are productive enough to cover a hiring cost. The matches for job stayers are a mixture of matches that survived previous periods of low aggregate productivity and matches created in recent periods of high productivity. Consequently, the distribution of match-specific productivity of job stayers stochastically dominates the distribution of match-specific productivity of new hires.

When aggregate productivity is low, the matches of new hires have high match-specific productivity, because only such matches are productive enough to cover a hiring cost. The previously created matches with low match-specific productivity are destroyed. The existing matches with medium and high match-specific productivity are productive enough to survive, even though some of them are not productive enough to cover a hiring cost. The matches of job stayers are a mixture of matches created in previous periods which are productive enough to survive, and matches created in recent periods of low productivity. Consequently, the distribution of match-specific productivity of new hires stochastically dominates the distribution of match-specific productivity of job stayers.

I calibrate the model using external sources to inform the value of a hiring cost and the distribution of match-specific productivity. I compare the cyclical properties of the model-generated wages and the observed wages, and the properties of job duration for generated job spells and the observed spells. The model-generated wages have similar cyclical properties as the observed wages: the wages of new hires are less procyclical than the wages of job stayers. Matches created when aggregate productivity are at a decreased risk of subsequent separation.

2.2 Related Literature

The key elements of the model I use are match-specific productivity and turnover costs. Both features appeared in the previous literature. However, their interaction and consequences for the cyclical properties of wages were unexplored.

2.2.1 Match-Specific Productivity

The match quality defined as the idiosyncratic productivity of a worker-firm pairing was popularized by Jovanovic (1979 a,b; 1984). In the Jovanovic learning model, the match quality is a pure experience good: it is assigned randomly when a job is created and its value is revealed over tenure by observed output. Moscarini (2005) embeds this idea into the Diamond-Mortensen-Pissarides search and matching model, with the match quality taking only one of two values. The consequences for wages in a steady state are considered: the selection on match quality moves workers to matches with higher perceived quality and higher wages, giving the wage distribution a long and fat right tail, which is observed empirically.

Pries and Rogerson (2005) combine a variant of the Jovanovic learning model, in which the match quality is partially an inspection and partexperience good, and the Diamond-Mortensen-Pissarides search and matching model to investigate the steady state effects of, among others, turnover costs in the form of dismissal costs. In this variant of the learning model, a firm and a worker receive a signal before a match is formed, giving them a probability of the match being bad or good. The match quality is then revealed gradually by output observations. Similarly to this paper, the higher dissmisal costs push up the threshold for the signal about match quality above which matches are accepted.

More generally, the standard assumption in the search and matching literature is that new matches start with the same match-specific productivity, which later evolves, as in Mortensen and Pissarides (1994), Pissarides (2009), and Fuijta and Ramey (2012). Matches were allowed to start with randomly drawn productivity in Mortensen (1982) and Mortensen and Nagypal (2007b). However, the consequences of the presence of match-specific productivity for the cyclical properties of wages were not investigated.

A paper closely related to mine is Gertler, Huckfeldt and Trigari (2016). They build a model with match-specific productivity, which takes two values, and endogenous on-the-job search. The model generates a procyclical selection effect for new hires from employment. An interesting implication is that jobs created by a job-to-job transition during downturns should be at an increased risk of ending with a subsequent job-to-job transition. The implication was not investigated in the paper.

The consequences of match quality selection for wages appear in a different context in Hagedorn and Manovskii (2013). They argue that when wages depend on current conditions and match-specific productivity, past selection over match quality makes wages appear to depend on past labor market conditions summarized by the lowest unemployment rate during a job spell. Their preferred proxies for match quality are derived from measures of labor market tightness during a job spell and an employment cycle. In future empirical work, I plan to use information on past and future labor market conditions to control for match quality in the estimation of cyclicality of wages, along the lines of Beaudry and DiNardo (1991) and Hagedorn and Manovskii (2013), but with a focus on the most adverse labor market conditions which a job survives.

2.2.2 Turnover Costs

Turnover (hiring or firing) costs were added to the search and matching model in Braun (2006), Nagypal (2007), Silva and Toledo (2009) and Yashiv (2006). Turnover costs improve the performance of the model by making firms' net profits more responsive to changes in productivity.

Muehlemann and Pfeifer (2016) use a German firm-level survey from the 2000s to assess the recruitment and adaptation costs generated by job creation. The average total hiring cost in Germany was equal to more than 2 months of wage payments, with two-thirds of this cost incurred when a worker was hired, and one-third generated by vacancy creation and screening of applications. I use the provided ratio of a hiring cost to wages in my model calibration. For the US, Dube et al. (2010) assess the average total hiring cost to be approximately 1.1 of the monthly wages in California, which suggests that the hiring cost should be twice as high in Germany as in the US.

A characteristic feature of the German labor market is that the firing costs are high. Unlike in the US, an employee with a permanent contract that is dismissed on operational grounds is entitled to severance pay equal to half of a monthly wage for each year of tenure, up to 12 monthly wages for most workers, and even more for older workers with long tenure.

2.3 Selection Effect: Stylized Example

In this section, I use a stylized example to illustrate the mechanism generating the cyclical properties of wages and job duration. Aggregate productivity takes two values, low y_1 and high y_2; match-specific productivity has three values z_1, z_2, and z_3, such that $z_1 < z_2 < z_3$; and agents are myopic, discounting with factor 0. I leave vacancy creation decision unspecified, assuming only that vacancies are created in both aggregate states, and that there are no more vacancies created in the low productivity state than in the high productivity state.

A worker in a match with match-specific productivity z produces zy when aggregate productivity is y, receiving a fraction τ of his output. His employer receives $(1-\tau)zy$. The worker quits if his wage τzy is lower than the unemployment benefit b.[2] The probability that an exogenous separation occurs is δ.

When an unemployed worker and a vacancy-posting firm meet, they draw value z of match-specific productivity from a fixed distribution. The firm has to incur a sunk cost h, but only if a job is created. The firm wants to create a job if its per-period earnings would cover the hiring cost, $(1-\tau)zy \geq h$. The worker wants the job if his wage would be no less than the unemployment benefit, $\tau zy \geq b$.

Figure 1 summarizes the model under parameter values ensuring that the match quality selection effect is present. The parameters have to satisfy the inequalities

$$z_3 \geq \frac{h}{(1-\tau)y_1} > z_2 \geq \frac{b}{\tau y_1} > z_1 \geq \frac{h}{(1-\tau)y_2} \tag{2.1}$$

which is possible. When aggregate productivity is high, all possible matches produce enough output to be preferable to unemployment for workers and to justify job creation for firms. There are

[2] For clarity of exposition, I assume that a firm and a worker split the match output zy, not the surplus $zy - b$. The reasoning goes through when they split the surplus instead.

no endogenous separations. When aggregate productivity is low, the lowest-productivity matches are destroyed, because workers find unemployment preferable. The medium-productivity matches are preferable to unemployment for workers, but are not productive enough to cover the hiring cost, which means that the existing medium-productivity matches survive but there no new medium-productivity matches.

In the low productivity state, there are no less separations than in the high state - endogenous separations happen only in the first period after a drop in aggregate productivity, and the rate of exogenous separations is constant. Under the assumption that vacancy creation does not increase in the low productivity state, and taking into account that some worker-firm meetings in the low state do not lead to match creation due to drawing low match-specific productivity, there is less job creation when aggregate productivity is low. Consequently, the unemployment rate rises in the low productivity state.

Because unemployment is higher when aggregate productivity is lower, the relationships between the model outcomes, the wages and job durations, and aggregate productivity translate into the relationships between the model outcomes and the unemployment rate. I show that the wages and job durations generated in a model that satisfies the condition (2.1) have the desired cyclical properties.

The relationship between the initial unemployment rate and the subsequent risk of separation is negative. The risk of exegenous separation is constant and independent of initial conditions. Only endogenous separations are those of workers that quit low-productivity matches when aggregate productivity is low.

I proceed to show that the wages of new hires are less procyclical than the wages of job stayers. The cyclical properties of wages result from the properties of the distributions of match-specific productivity for new hires and job stayers. The distribution of match-specific productivity for new hires stochastically dominates the distribution of match-specific productivity for job stayers when aggregate productivity is low, but the reverse happens when aggregate productivity is high.

The distribution of match-specific productivity for new hires is the same as the underlying distribution of match-specific productivities when aggregate productivity is high. When aggregate productivity is low, all match-specific productivities of new hires are equal to z_3. Consequently, the mean wages of new hires are $\overline{w}_2^H = \tau y_2 \mathbb{E}z$ and $\overline{w}_1^H = \tau y_1 z_3$, in upturns and in downturns, respectively.

When aggregate productivity is high, job stayers belong to one of three groups: workers that were hired during the current upturn, with the same match-specific productivity distribution as the underlying distribution of match-specific productivities, which mean is $\mathbb{E}z$; workers that were hired during a previous upturn and remained employed during a downturn, with a match-specific productivity distribution that is a truncation of the underlying distribution of match-specific productivities without z_1, which mean is $\mathbb{E}z|z > z_1$; and workers that were hired during a previous downturn, who are employed exclusively in matches with productivity z_3. Let the fractions of the second and third group of workers in the total number of employed workers be π and π'.

The distribution of match-specific productivity for job stayers during upturns is a mixture of three distributions. Two of these distributions stochastically dominate the match-specific productivity distribution for new hires, one of them is the same distribution. Consequently, the distribution of match-specific productivity for job stayers stochastically dominates the distribution of match-specific productivity for new hires.

The mean wage of job stayers is

$$\overline{w}_2^S(\pi, \pi') = (1 - \pi - \pi')\tau y_2 \mathbb{E}z + \pi \tau y_2 \mathbb{E}z|z > z_1 + \pi' \tau y_2 z_3$$

where π, $\pi' \in [0, 1]$, such that $\pi + \pi' \in [0, 1]$, depend on the rate of exegenous separations, and history of vacancy creation and of aggregate states. The mean wage of job stayers, $\overline{w}_2^S(\pi, \pi')$, is higher than the mean wage of new hires, $\overline{w}_2^H = \tau y_2 \mathbb{E}z$, as long as $\pi + \pi' < 1$.

When aggregate productivity is low, job stayers belong to one of two groups: workers that were hired during the current or a previous downturn, who are employed exclusively in matches with productivity z_3; or workers that were hired during a previous upturn and remain employed during a downturn, with a match-specific productivity distribution that is a truncation of the underlying distribution of match-specific productivities without z_1, which mean is $\mathbb{E}z|z > z_1$. Let the fraction of the second group of workers in the total number of employed workers be γ.

The distribution of match-specific productivity for job stayers during downturns is a mixture of 3 distributions. One of these distributions is stochastically dominated by the match-specific productivity distribution for new hires, the other two are the same distribution. Consequently, the distribution of match-specific productivity for new hires stochastically dominates the distribution of match-specific productivity for job stayers.

The mean wage of job stayers is

$$\overline{w}_1^S(\gamma) = (1-\gamma)\tau y_1 z_3 + \gamma \tau y_1 \mathbb{E}z|z > z_1$$

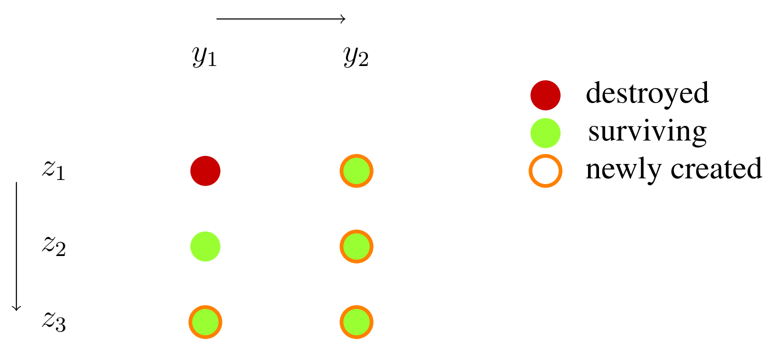
where $\gamma \in [0, 1]$ depends on the rate of exegenous separations, and history of vacancy creation and of aggregate states. The mean wage of job stayers, $\overline{w}_1^S(\gamma)$, is lower than the mean wage of new hires, $\overline{w}_1^H = \tau y_1 z_3$, as long as $\gamma > 0$.

The inequalities $\overline{w}_1^S(\gamma) < \overline{w}_1^H$ and $\overline{w}_2^H < \overline{w}_2^S(\pi, \pi')$ imply that

$$\frac{\overline{w}_1^S(\gamma) - \overline{w}_2^S(\pi, \pi')}{\overline{w}_2^S(\pi, \pi')} < \frac{\overline{w}_1^H - \overline{w}_2^H}{\overline{w}_2^H}, \quad \frac{\overline{w}_2^H - \overline{w}_1^H}{\overline{w}_1^H} < \frac{\overline{w}_2^S(\pi, \pi') - \overline{w}_1^S(\gamma)}{\overline{w}_1^S(\gamma)}. \tag{2.2}$$

When $\overline{w}_1^H < \overline{w}_2^h$, which is guaranteed by assuming that $y_1 z_3 < y_2 \mathbb{E}z$, inequalities (2.2) show that, in percentage terms, the mean wages of new hires respond less to aggregate productivity than

Figure 2.1: Match Quality Selection Effect



the mean wages of job stayers. Consequently, regressing the logarithms of wages on aggregate productivity or unemployment, leads to the conclusion that the wages of new hires are less procyclical than the wages of job stayers, even though all wages are equally and fully responsive to aggregate conditions.

2.4 Model

I build a variant of the Diamond-Mortensen-Pissarides search and matching model. The two crucial elements of the model are match-specific productivity and a hiring cost.

2.4.1 Model Outline

There is a continuum of workers with measure one and a continuum of firms. Each firm turns one unit of labor into $r(y, z)$ units of output, where r is an increasing function of aggregate productivity y and match-specific productivity z. I use the standard production function $r(y, z) = yz$. The unemployed workers receive a flow benefit b.

The workers and firms are risk-neutral. They maximize the expected sum of periodical incomes. The discount factor is β.

The aggregate productivity, y, is the same for all firms, with values in the set $Y = \{y_1, y_2, .., y_{N_Y}\}$, where $y_1 < y_2 < ... < y_{N_Y}$ and $N_Y \geq 2$. The aggregate productivity y is updated to $\hat{y}$ at the beginning of the next period with probability $f_Y(y, \hat{y})$, where $f_Y : Y^2 \rightarrow [0, 1]$.

The match-specific productivity, z, with values in the set $Z = \{z_1, z_2, .., z_{N_Z}\}$, where $z_1 < z_2 < ... < z_{N_Z}$ and $N_Z \geq 2$, is fixed for each match after being drawn from a probability distribution with a cumulative distribution function F_Z . The match-specific productivity is drawn when a worker and a firm meet, but before a worker is hired.

The notation for value functions is standard. The value of match to the firm, the value of match to the worker, the value of unemployment to the worker, and the match surplus are denoted as $J(y, z)$, $W(y, z)$, $U(y)$, and $S(y, z) = J(y, z) + W(y, z) - U(y)$.

The Nash bargaining divides the match surplus. The contract between a firm and its employee specifies the wage $w(y, z)$. The wage equalizes the worker's surplus $W(y, z) - U(y)$ with $\tau S(y, z)$, where $\tau \in [0, 1]$ is the workers' bargaining power parameter.

There is a hiring cost $h \geq 0$ that has to paid in the first period of employment. This is a sunk cost that is incurred only if a job is created and that does not enter into the match surplus.

The firms create vacancies which meet workers through a frictional meeting process. The number of meetings is determined by a CRS matching function $M(u, v)$, which depends on the mass of created vacancies, v, and the mass of workers looking for jobs, u. The probabilities that the workers and vacancies meet is $M(u, v)/u$ for workers and $M(u, v)/v$ for the vacancies, which can be written as functions of labor market tightness $\theta = v/u$. An unemployed worker meets a vacancy with probability $p(\theta) = M(1, \theta)$, a vacancy meets a worker with probability $q(\theta) = M(\theta^{-1}, 1)$.

The zero profit condition determines vacancy creation. The firms' expected profit from vacancy creation depends on the probability of meeting a worker and the expected value of meeting a worker, denoted as $\tilde{J}(y)$. If the expected value exceeds the cost of vacancy creation, $c > 0$, vacancies are created until the expected profit is driven to zero. If the expected value is less than the cost of vacancy creation, no vacancies are created. Labor market tightness is determined in the equilibrium as

$$\theta(y) = \begin{cases} q^{-1}(c/\tilde{J}(y)), & \text{if } \tilde{J}(y) \geq c \\ 0. & \text{if } \tilde{J}(y) < c. \end{cases} \tag{2.3}$$

Matches are destroyed if the surplus $S(y, z)$ is negative and with the exogenous separation probability $\delta \in (0, 1)$. For simplicity, I assume that the workers who lose a job cannot find a new one in the same period.

2.4.2 Value Functions

The match surplus S is a sum of the firm's surplus, J, and the worker's surplus, $W - U$, where W and U are the value of employment and unemployment. The Nash bargaining leads to the condition

$$\frac{J(y,z)}{1-\tau} = S(y,z) = \frac{W(y,z) - U(y,z)}{\tau}.$$

The value accruing to an unemployed worker is

$$\begin{aligned} U(y) =& b + \beta\mathbb{E}\Big[\big(1 - p(\theta(\hat{y}))\big)U(\hat{y}) \\ & + p(\theta(\hat{y})) \int \mathbb{1}\{(1-\tau)S(\hat{y},z) < h\} dF_Z(z) U(\hat{y}) \\ & + p(\theta(\hat{y})) \int \mathbb{1}\{(1-\tau)S(\hat{y},z) \geq h\} W(\hat{y},z) dF_Z(z)\Big] \end{aligned}$$

which can be rewritten as

$$U(y) = b + \beta\mathbb{E}\Big[U(\hat{y}) + p(\theta(\hat{y})) \int \mathbb{1}\{(1-\tau)S(\hat{y},z) \geq h\} \tau S(\hat{y},z) dF_Z(z)\Big].$$

The value accruing to an employed worker is

$$\begin{aligned} W(y,z) =& w(y,z) + \beta\mathbb{E}\Big[\delta U(\hat{y}) \\ & + (1-\delta)\mathbb{1}\{S(\hat{y},z) < 0\} U(\hat{y}) \\ & + (1-\delta)\mathbb{1}\{S(\hat{y},z) \geq 0\} W(\hat{y},z)\Big] \end{aligned}$$

which can be rewritten as

$$W(y,z) = w(y,z) + \beta\mathbb{E}\Big[U(\hat{y}) + (1-\delta)\mathbb{1}\{S(\hat{y},z) \geq 0\}\tau S(\hat{y},z)\Big].$$

The value accruing to a firm employing a job stayer is

$$J(y,z) = r(y,z) - w(y,z) + \beta\mathbb{E}(1-\delta)\mathbb{1}\{S(\hat{y},z) \geq 0\}J(\hat{y},z)$$

which can be rewritten as

$$J(y,z) = r(y,z) - w(y,z) + \beta\mathbb{E}(1-\delta)\mathbb{1}\{S(\hat{y},z) \geq 0\}(1-\tau)S(\hat{y},z).$$

The surplus S can be rewritten as

$$\begin{aligned} S(y,z) = & r(y,z) - b + \beta\mathbb{E}\Big[(1-\delta)\mathbb{1}\{S(\hat{y},z) \geq 0\}S(\hat{y},z) - \\ & p(\theta(\hat{y}))\int \mathbb{1}\{(1-\tau)S(\hat{y},\hat{z}) \geq h\}\tau S(\hat{y},\hat{z})dF_Z(\hat{z})\Big]. \end{aligned} \tag{2.4}$$

The expected value of meeting a worker is

$$\tilde{J}(y) = \int \mathbb{1}\{(1-\tau)S(y,z) \geq h\}((1-\tau)S(y,z) - h)dF_Z(z). \tag{2.5}$$

2.4.3 Equilibrium

The equations (2.3)-(2.5) define a functional operator. An equilibrium is a surplus function S satisfying the equation (2.4), where a market tigthness function θ is dictated by the equations (2.5) and (2.3). The equilibrium is a fixed point of a functional operator.

The equilibrium operator is not continuous, which is the the only obstacle that precludes proving the equilibrium existence with the use of the Brouwer's fixed-point theorem.[3] I consider a

[3]The standard method of proving the equilibrium existence and uniqueness by proving that the equilibrium operator satisfies Blackwell's sufficient conditions, as in Mortensen and Nagypal (2007b), is not applicable, because terms of the type $\mathbb{1}\{x \geq 0\}x$ introduce non-convexity.

proxy of the model. In the proxy model, the equilibrium operator is continuous. I prove the equilibrium existence for the proxy model in Appendix A. If, in the equilibrium, the proxy model reduces to the original model, then the equilibrium of the proxy model is also an equilibrium of the original model. The discontinuity of the equlibrium operator stems from the presence of a hiring cost that is excluded from the match surplus. The existence of an equilibrium in a model in which a hiring cost enters the match surplus can be proved directly.

I use the Brouwer's theorem, which does not guarantee the equilibrium uniqueness and is not constructive. However, I take the advantage of the properties of the equilibrium operator, which can be decomposed in a sum of its increasing and decreasing parts. I adopt a method that numerically narrows the space of potential equilibria, which I discuss in Appendix B.

2.4.4 Match Creation and Match Survival Thresholds

When aggregate productivity is y, a match with match-specific productivity z is not endogenously destroyed if the condition $S(y, z) \geq 0$ is satisfied, and can be created if the condition $S(y, z) \geq h$ is satisfied. When $S(y, z)$ is increasing in the second argument, z, there are match-specific productivity thresholds for match survival and match creation,

$$z^s(y) = \min_{z \in Z}\{S(y, z) \geq 0\}$$

and

$$z^c(y) = \min_{z \in Z}\{S(y, z) \geq h\},$$

with the following properties: $z > z^s(y)$ implies that $S(y, z) \geq 0$ and a match with match-specific productivity z is not endogenously destroyed; $z > z^c(y)$ implies that $S(y, z) \geq h$ and a match with match-specific productivity z can be created; and $z^c(y) \leq z^s(y)$, the threshold for match creation is more demanding than for match survival. When $S(y, z)$ is also increasing in the first argument, y, the thresholds are non-increasing functions of aggregate productivity, y.

For the highest aggregate productivity, y_{N_Y}, it can be assumed without loss of generality that the thresholds for match survival and match creation coincide, $z^c(y_{N_Y}) = z^s(y_{N_Y}) = z_1$, which together with $z^s(y) \leq z^c(y)$ implies that

$$z^c(y_{N_Y}) = z^s(y_{N_Y}) \leq z^c(y) \leq z^s(y) \tag{2.6}$$

for any aggregate productivity y.

2.4.5 Match-Specific Productivity for New Hires and Job Stayers

To illustrate the selection effect it is sufficient to consider two aggregate productivity states, low y_1 and high y_2. In this section, I show that the selection effect is present if there are some matches that can survive but cannot be created when aggregate productivity is low, $z^s(y_1) < z^c(y_1)$, which together with (2.6) implies that

$$z^s(y_1) < z^c(y_1) \leq z^c(y_2) = z^s(y_2). \tag{2.7}$$

There are four groups of workers whose match-specific productivity distributions I consider, new hires and job stayers when aggregate productivity is low and when aggregate productivity is high.

A match-specific productivity distribution for new hires, $H(z; y)$, is a truncation of the underlying match-specific productivity distribution, F, that restricts its domain to match-specific productivities that are above the match creation threshold

$$H(z; y) = \frac{F(z)}{1 - F(z^c(y))}.$$

For high aggregate productivity, y_2, the distributions $H(z; y)$ and $F(z)$ coincide.

The inequalities (2.7) guarantee that there are some matches that can survive but cannot be created when aggregate productivity is low. The match-specific productivity distribution for such matches is

$$P(z) = \frac{F(z)}{1 - F(z^s(y_1))}.$$

When aggregate productivity is low, job stayers belong to one of two groups: workers that were hired during the current or a previous episode of low productivity, whose match-specific productivity distribution is $H(z; y_1)$; or workers that were hired during an episode of high productivity and remain employed during a downturn, whose match-specific productivity distribution is $P(z)$. The match-specific productivity distribution for job stayers is

$$G(z; y_1, \gamma) = (1 - \gamma)H(z, y_1) + \gamma P(z)$$

where $\gamma \in [0, 1]$, the fraction of the second group of workers, decreases in the duration of low-productivity episode.

When aggregate productivity is high, job stayers belong to one of three groups: workers that were hired during the current episode of high productivity, whose match-specific productivity distribution is $H(z; y_2)$; workers that were hired during a previous episode of high productivity and remained employed during a previous episode of low productivity, whose match-specific productivity distribution is $P(z)$; or workers that were hired during a previous episode of low productivity, whose match-specific productivity distribution is $H(z; y_1)$. The match-specific productivity distribution for job stayers is

$$G(z, y_2, \pi, \pi') = (1 - \pi - \pi')H(z, y_2) + \pi P(z) + \pi' H(z, y_1)$$

where the fractions of the second and third group of workers are π and π', which decrease in the duration of high-productivity episode.

The inequalities (2.7) imply that the match-specific productivity distributions can be ordered the sense of first-order stochastic dominance. The ordering $H(z;y_2), P(z) \prec H(z;y_1)$ implies the ordering

$$H(z;y_2) \prec G(z,y_2,\pi,\pi'), G(z;y_1,\gamma) \prec H(z;y_1). \tag{2.8}$$

The first-order stochastic dominance ordering (2.8) implies inequalities between the means of the four distributions. The mean match-specific productivity for new hires when aggregate productivity is high is the lowest of the four means, the mean match-specific productivity for new hires when aggregate productivity is low is the of the four means, and the means for job stayers lie between these two extremes. When the means of $H(z;y_2)$, $G(z,y_2,\pi,\pi')$, $G(z;y_1,\gamma)$ and $H(z;y_1)$ are denoted as $\bar{z}_2^H$, $\bar{z}_2^S(\pi,\pi')$, $\bar{z}_1^S(\gamma)$ and $\bar{z}_1^H$, the inequalities between the means are

$$\bar{z}_2^H < \bar{z}_2^S(\pi,\pi'),\ \bar{z}_1^S(\gamma) < \bar{z}_1^H \tag{2.9}$$

The inequalities (2.9) lead to a conclusion that the mean match-specific productivity for new hires is countercyclical, rising when aggregate productivity is lower, and that its cyclical changes are smaller than the cyclical changes in the mean match-specific productivity for job stayers.

2.4.6 Calibration

The calibration is at a monthly frequency. The model has 11 parameters, summarized in Table 2.1. For 4 parameters I use paremeters values that are common in the literature. I calibrate 7 remaining parameters using external information.

Table 2.1: Model Parameters

Value	Description	Target/Source
$h = 1.9$	hiring cost	Muehlemann and Pfeifer (2016)
$\sigma = 0.3$	sd of log match productivity	Card, Heining, and Kline (2013)
$\beta = 0.9966$	discount factor	standard, annual interest rate 4.17%
$\eta = 0.5$	matching function elasticity	standard, Pissarides and Petrongolo (2001)
$\tau = 0.5$	workers' bargaining power	standard, Hosios' condition, $\tau = \eta$
$\sigma_y = 0.02$	aggregate productivity sd	standard, Shimer (2005)
$\rho = 1/24$	transition probabilities	standard, 2-year long recessions
$\delta = 0.0095$	exogenous separation rate	separations, Elsby et al. (2013), Nordmeier (2014)
$b = 0.55$	unemployment benefit	Krause and Uhlig (2012)
$c = 0.42$	vacancy creation cost	un, job finding, Elsby et al. (2013), Nordmeier (2014)
$\kappa = 0.35$	matching efficiency	un, job finding, Elsby et al. (2013), Nordmeier (2014)

The key features of the model are a hiring cost and match-specific productivity. I use external sources to inform the value of the hiring cost and the match-specific productivity distribution.

The hiring cost h is calibrated to be approximately 1.3 of the mean monthly wage, as calculated by Muehlemann and Pfeifer (2016) from a survey of German firms.

I follow the literature and assume that match-specific productivity has a lognormal distribution with a standard deviation σ. The data moment used to calibrate σ is the standard deviation of the residual log wages, taken from Card, Heining, and Kline (2013), who estimated the Mincer equation for log wages using the whole universe of German labor market biographies.

The parameters β, η, τ and ρ have values standard in the literature. The aggregate productivity is either low, $1 - \sigma_y$, or high, $1 + \sigma_y$. Tha parameter σ_y targets the standard deviation 0.02 of log labor productivity, as in Shimer (2005).

The exogenous separation rate $\delta = 0.095$ is equal to the lower values of the monthly separation rate in the 2000s calculated in Nordmeier (2014) and consistent with previous calculations in Elsby et al. (2013).

The unemployment benefit b is calibrated to target 0.4 of mean monthly labor income, as in Krause and Uhlig (2012) for the post-Hartz period.

I use the standard matching function $M(u, v) = \kappa u^{\eta} v^{(1-\eta)}$.[4]. The vacancy creation cost c and the matching function efficiency parameter κ are jointly calibrated to match the mean monthly job finding rate calculated in Nordmeier (2014) and Elsby et al. (2013), around $0.055 - 0.07$, and the mean monthly unemployment rate 0.09.

The model outcomes, summarized and compared with target moments in Table 2.2, are generated from simulations of the model with 2400 monthly observations on 10000 workers with 51 possible match-specific productivities.

Table 2.2: Model Fit

Outcome	Target	Description
1.29	1.3	hiring cost relative to $\overline{w}$
0.11	0.14	sd of (residual) log wages
0.37	0.4	unemployment benefit relative to $\overline{w}$
0.12	0.09	unemployment rate
0.01	0.01	separation rate
0.07	0.055-0.07	job finding rate

Notes: $\overline{w}$ denotes mean labor income.

2.4.7 Properties of Model-Generated Data

The first empirical finding of the previous chapter is that the wages of new hires are less procyclical than the wages of job stayers. To confirm that this cyclical property arises in the model, I estimate

[4]The function has to be truncated by the condition $M(u, v) \leq min\{u, v\}$, which is equivalent to a restriction $\theta \in [\kappa^{1/\eta}, \kappa^{1/(1-\eta)}]$

the wage equation

$$log\, w_{it} = \pi u_t + \pi_U NH_U(i,t)u_t + \gamma NH_U + \epsilon_{it} \tag{2.10}$$

where w_{it} is the wage paid in period t in match i, u_t is the unemployment rate, and $NH_U(i,t)$ is an indicator variable that takes value one for new hires, using simulated wages.

Table 2.3 shows the averaged estimates from Equation 2.10. The wages have the key cyclical property matching the empirical findings from the previous chapter: the estimated incremental effect $\hat{\pi}_U = 0.46$ is positive and significant, and of similar magnitude as the analogous estimate in the previous chapter. For all simulations, the estimates are significant and have the desired cyclical properties.

Table 2.3: Wage Cyclicality Estimates for Model-Generated Wages

$\hat{\pi}$	-1.85
$\hat{\pi}_U$	0.46

Notes: Average values from 5 simulations of 2400 monthly observations on 20000 workers with 51 possible match-specific productivities.

To complete the analysis of cyclical properties of wages, I solve and simulate the model without a hiring cost, setting $h = 0$. Table 2.4 shows averages of estimates of Equation 2.10 for simulated wages. The baseline estimate of wage cyclicality, $\hat{\pi}$, decreases from -1.85 to -2.54. The incremental effect for wages of new hires, $\hat{\pi}_U$, is small and insignificant in all simulations.

The differences between the cyclical properties for the model with and without a hiring cost are expected. The thresholds for match creation and match maintenance coincide in this model, which implies the wages of job stayers and new hires have the same cyclicality. In the model with a hiring cost, when aggregate productivity is low, a fraction of job stayers are workers that were hired during the current episode of low productivity, whose match-specific productivity undergoes the strongest selection, which decreases the cyclicality of wages of job stayers.

Table 2.4: Wage Cyclicality Estimates for Model-Generated Wages, No Hiring Cost

$\hat{\pi}$	-2.54
$\hat{\pi}_U$	0.09

Notes: Average values from 5 simulations of 2400 monthly observations on 20000 workers with 51 possible match-specific productivities.

The second empirical finding of the previous chapter is that unemployment at the beginning of employment and the subsequent risk of separation are negatively related. For comparison with model outcomes, I estimate the Cox (1972) model using simulated unemployment and job durations. The hazard rate h_{id} for match i after d periods from hiring takes the functional form

$$h_{id} = \tilde{h}_d exp(\alpha u_i^{start} + \epsilon_{id}) \tag{2.11}$$

where $\tilde{h}_d$ is the baseline hazard rate common to all matches and u_i^{start} is the unemployment rate at the creation of match i. Table 2.5 shows averages of estimates of Equation 2.11.

Table 2.5: Estimates for Job Duration

$\hat{\alpha}$	-0.61

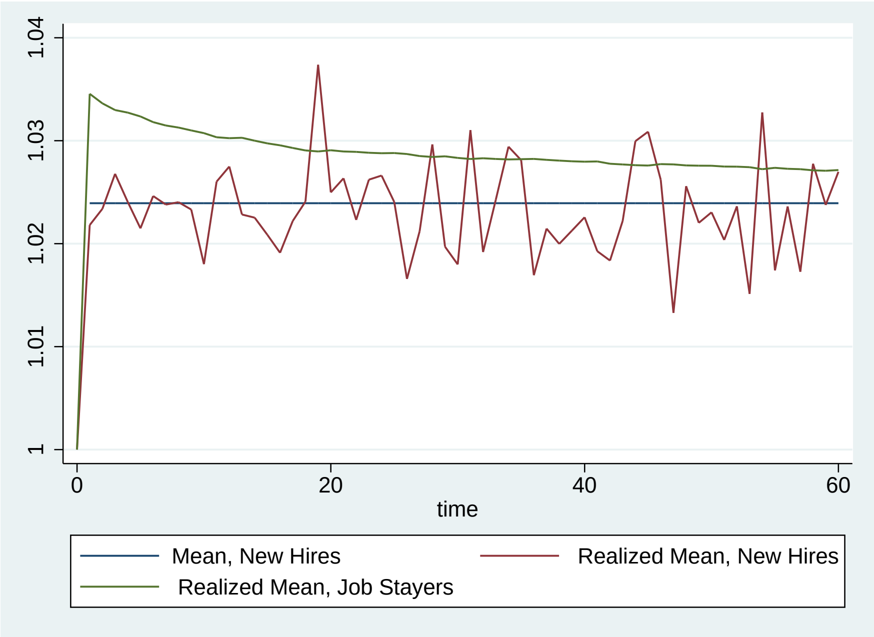
Notes: Average values from 5 simulations of 2400 monthly observations on 20000 workers with 51 possible match-specific productivities.

Finally, I illustrate the responses of wages to productivity changes: Figure 2.2 shows the simulated response of mean wages to a positive shock to aggregate productivity, and Figure 2.3 shows the simulated response of mean wages to a negative shock to aggregate productivity.

As seen in Figure 2.2, after the shock the mean wages of job stayers and new hires increase. The mean wages wages of job stayers are higher than for new hires, due to the presence of workers that were survived or were hired during previous episodes of low productivity, and gradually decrease to the mean wages of new hires as the share of workers hired during the current episode of high productivity.

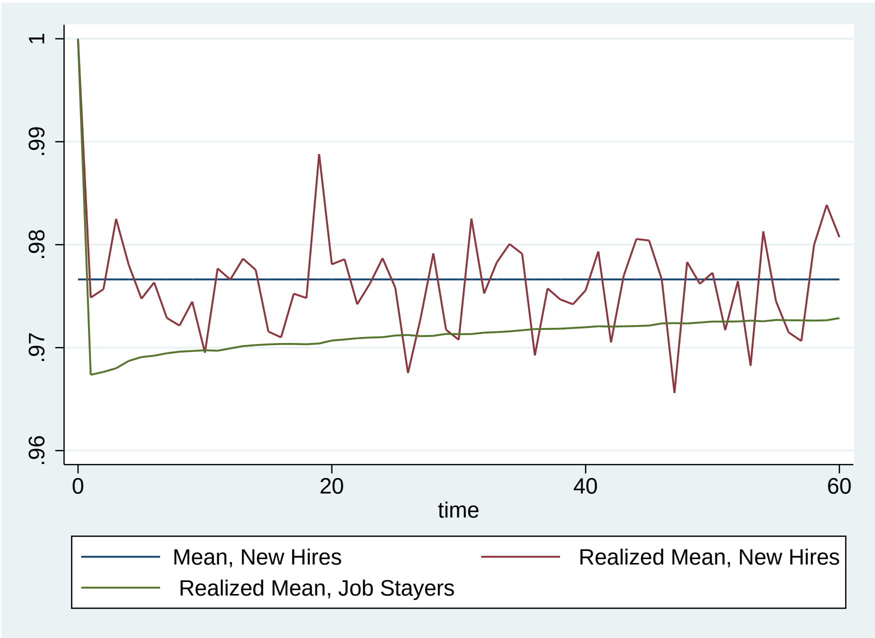
Conversely, as Figure 2.3 shows, after the shock the mean wages of job stayers and new hires decrease. The mean wages wages of job stayers are lower than for new hires, due to the presence of workers that were hired during previous episodes of high productivity, and gradually increase to the mean wages of new hires as the share of workers hired during the current episode of low productivity.

Figure 2.2: Response of Wages to a Positive Aggregate Shock



Notes: The series are normalized by the mean wage for new hires in the low productivity state. The series start with the economy in the low productivity state and depict a simulated response of the mean wage for job stayers and the mean wages for new hires, realized and expected, to a positive change in aggregate productivity.

Figure 2.3: Response of Wages to a Negative Aggregate Shock



Notes: The series are normalized by the mean wage for new hires in the high productivity state. The series start with the economy in the high productivity state and depict a simulated response of the mean wage for job stayers and the mean wages for new hires, realized and expected, to a negative change in aggregate productivity.

2.5 Conclusions

The match quality selection effect arises in a standard Diamond-Mortensen-Pissarides search and matching model with two additional features: match-specific productivity and turnover costs. The cyclical selection on match quality explains the empirical findings of the previous chapter, the wages of new hires being less procyclical than the wages of job stayers, and a negative relationship between the initial unemployment rate and the subsequent risk of separation.

More generally, these two fairly realistic features could generate the same selection effect in models with different wage-setting mechanisms. An example would be a model with staggered multiperiod Nash bargaining in which workers' wages are negotiated for the first time when they are hired.[5] Without the selection effect, the wages of new hires would be more procyclical than the wages of job stayers, which are not fully flexible. With the selection effect induced by match-specific productivities and turnover costs, the observed procyclicality of the wages of new hires relative to job stayers would be attenuated. The estimation of the cyclicality of model-generated wages could lead to an incorrect conclusion that the wages of new hires were no more or not much more procyclical than the wages of job stayers.

The empirical results of the previous chapter suggest that the match quality selection effect is stronger for hires from employment than from unemployment. The on-the-job search can be incorporated into the model to account for job-to-job transitions. In the present form, the model would not generate the stronger selection effect for hires from employment than for hires from unemployment. However, a conceptually easy modification should resolve this issue. For simplicity, I made match-specific productivity an inspection good, known to workers and firms immediately upon meeting. I could relax this assumption, making match-specific productivity partially an ex-

[5]Unlike Gertler and Trigari (2009), where workers hired in-between wage renegotiations receive the ongoing wage.

perience good. Then, worker-firm pairs receive a signal about match-specific productivity upon meeting. If they agree to form a match, the underlying productivity is revealed during first few months of its duration.[6] For hires from unemployment, the same force driving the selection effect in the baseline model appears in the generalized model. For hires from employment, the selection effect is enhanced: during downturns, the employed workers are concerned about a risk of job loss in a new match, since unemployment spells are longer in expectation, and demand a higher signal about match quality to accept an offer of a job-job transition.

[6]This is consistent with the observation that risk of separation is elevated during first few months on job, and goes down sharply afterwards.

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Appendix A: Equilibrium Existence

The equilibrium operator, denoted as $\mathcal{T}$, is defined by the equations (2.3)-(2.5). I use notation $P(y) = p(\theta(y))$ for the composite vacancy-meeting probability, and subscript S for the dependence on S, writing $\mathcal{T}$ as

$$\begin{aligned}\mathcal{T}S(y,z) =& r(y,z) - b + \beta\mathbb{E}\Big[(1-\delta)\mathbb{1}\{S(\hat{y},z) \geq 0\}S(\hat{y},z) - \\ & P^S(\hat{y})\int \mathbb{1}\{(1-\tau)S(\hat{y},\hat{z}) \geq h\}\tau S(\hat{y},\hat{z})dF_Z(\hat{z})\Big],\end{aligned}$$

where

$$\theta^S(y) = \begin{cases} q^{-1}(c/\tilde{J}^S(y)), & \text{if } \tilde{J}(y) \geq c \\ 0. & \text{if } \tilde{J}(y) < c \end{cases}$$

and

$$\tilde{J}^S(y) = \int \mathbb{1}\{(1-\tau)S(y,z) \geq h\}((1-\tau)S(y,z) - h)dF_Z(z).$$

The operator $\mathcal{T}$ is not continuous. There are at most two sources of discontinuity: the components $\mathbb{1}\{(1-\tau)S(y,z) \geq h\}\tau S(y,z)$ and, potentially, the vacancy-meeting probability $P^S(y)$.[7]

In the proxy model, I replace the indicator function $\mathbb{1}\{(1-\tau)S(y,z) \geq h\}$ by a function defined as

$$a^S(y,z) = \begin{cases} 0, & \text{if } (1-\tau)S(y,z) - h \leq 0 \\ \frac{1}{d}\big((1-\tau)S(y,z) - h\big), & \text{if } 0 \leq (1-\tau)S(y,z) - h \leq d \\ 1, & \text{otherwise,} \end{cases}$$

where d is a small positive number.

The function a has an intuitive explanation in the context of job creation decisions: when a firm's share of surplus does not cover the hiring cost, a job is not created; when a firm's share of

[7] The components $\mathbb{1}\{S(y,z) \geq 0\}S(y,z)$ and $\mathbb{1}\{(1-\tau)S(y,z) \geq h\}((1-\tau)S(y,z) - h)$ are continuous with respect to S, similarly to a function $\mathbb{1}\{x \geq 0\}x$, which is continuous with respect to x.

surplus is noticeably higher than the hiring cost, a job is created; when a firm's share of surplus is only slightly higher than the hiring cost, a job creation decision is randomized, with the creation probability increasing in the net profit from job creation.

The second potential source of discontinuity is the vacancy-meeting probability, $P^S(y)$. Under certain regularity conditions on q and p, which are satisfied for a matching function $M(u,v) = \frac{uv}{(u^\eta+v^\eta)^{1/\eta}}$, the function $P^S(y)$ depends continuosly on S. However, for the calibration exercise I use the Cobb-Douglas matching function $M(u,v) = \kappa u^\eta v^{(1-\eta)}$, which makes $\theta^S(y)$ jump at $\tilde{J}^S(y) = c$. In this case, I have to replace the original vacancy-meeting probability, which is

$$P^S(y) = \kappa^{1/\eta}\Big(\frac{\tilde{J}^S(y)}{c}\Big)^{(1-\eta)/\eta}\mathbb{1}\{\tilde{J}^S(y) \geq c\}$$

by

$$\tilde{P}^S(y) = \kappa^{1/\eta}\Big(\frac{\tilde{J}^S(y)}{c}\Big)^{(1-\eta)/\eta}\alpha^S(y) \tag{2.12}$$

where

$$\alpha^S(y) = \begin{cases} 0, & \text{if } c \geq \tilde{J}(y) \\ \frac{1+e}{-e}\frac{c}{\tilde{J}(y)} + \frac{1+e}{e}, & \text{if } c + ce \geq \tilde{J}(y) \geq c \\ 1, & \text{if } \tilde{J}(y) \geq c + ce, \end{cases}$$

where e is a small positive number. The replacement function $\tilde{P}^S(y)$ is equal to $P^S(y)$ when $\tilde{J}^S(y) \notin (c, c+ce)$ and depends continuously on S.[8] This modification corresponds to a situation where some workers decide against looking for a job when economic conditions are so bad that the net expected firm's profit from vacancy creation conditional on meeting a worker is close to zero, and where the proportion of such workers approaches zero continuously when the net expected firm's profit from vacancy creation conditional on meeting a worker approaches zero.

[8]Truncating the matching function $M(u,v) = \kappa u^\eta v^{(1-\eta)} \leq min\{u,v\}$ leads to restriction $P^S(y),\ \tilde{P}^S(y) \leq 1$.

I define the proxy equilibrium operator as

$$\begin{aligned}\tilde{\mathcal{T}}S(y,z) =& r(y,z) - b + \beta\mathbb{E}\Big[(1-\delta)\mathbb{1}\{S(\hat{y},z)\geq 0\}S(\hat{y},z) - \\ &\tilde{P}^S(\hat{y})\int a^S(\hat{y},\hat{z})\tau S(\hat{y},\hat{z})dF_Z(\hat{z})\Big],\end{aligned}$$

where $\tilde{P}^S = P^S$ if functions $p,\ q$ satisfy certain regularity conditions, and where $\tilde{P}^S$ is defined by equation (2.12) for the Cobb-Douglas matching function.

An equilibrium of the (proxy) model is a fixed point of an operator, $\tilde{\mathcal{T}}$, that maps a functional space, $\mathcal{S}$, into itself. To prove the existence of an equilibrium using the Brouwer's fixed point theorem, I show that the space $\mathcal{S}$ contains its own image under $\tilde{\mathcal{T}}$, that the space is convex and compact, and that the operator $\tilde{\mathcal{T}}$ is continuous.

I define the space of potential surplus functions, $\mathcal{S}$, by the condition $S \in \mathcal{S}$ iff $S : Y \times Z \to [\underline{S}, \overline{S}]$. The space is endowed with the maximum norm. The bounds

$$\overline{S} = \big(r(y_{N_Y}, z_{N_Z}) - b\big)/\big(1-(1-\delta)\beta\big)$$

and

$$\underline{S} = r(y_1, z_1) - b - \beta\tau\overline{S}.$$

are such that the space $\mathcal{S}$ contains its own image under $\tilde{\mathcal{T}}$. It is easily checked that if $\underline{S} \leq S(y,z) \leq \overline{S}$ for all y, z, then $\underline{S} \leq \tilde{\mathcal{T}}S(y,z) \leq \overline{S}$ for all y, z follows .

Compactness of $\mathcal{S}$ follows from the Bolzano-Weierstrass theorem applied to $[\underline{S}, \overline{S}]^{|Y\times Z|}$, since set $Y \times Z$ is finite. Convexity of $\mathcal{S}$ is obvious.

It remains to prove that the operator $\tilde{\mathcal{T}}$ is continuous.

Lemma 2.5.1. *The operator $\tilde{\mathcal{T}}$ is continuous, if (1) $\tilde{P}^S = P^S$, p is a differentiable function with a derivative which is bounded and bounded away from zero, and q an invertible and differentiable function with a derivative that is bounded away from zero on $[0, A]$, for all $A < \infty$, with $q(0) = 1$. The operator $\tilde{\mathcal{T}}$ is continuous, if (2) $\tilde{P}^S$ is defined by the equation (2.12).*

Proof. It is sufficient to show that there exists constant D such that

$$|\mathcal{T}S_2(y,z) - \mathcal{T}S_1(y,z)| \leq D||S_1 - S_2||$$

for all $S_1, S_2 \in \mathcal{S}$ and all $y \in Y$, $z \in Z$.

Examination of the definition of $\tilde{\mathcal{T}}$ reveals that it suffices to prove that

$$|\tilde{P}^{S_2}(y) - \tilde{P}^{S_2}(y)| \leq C||S_2 - S_1||.$$

for some constant C.

In the case (1), when functions $p,\ q$ satisfy some regularity conditions, it is sufficient to prove the existence of constants A, B such that

$$|\theta^{S_2}(y) - \theta^{S_1}(y)| \leq A||S_1 - S_2||,$$

$$|p(\theta^{S_2}(y)) - p(\theta^{S_1}(y))| \leq B|\theta^{S_2}(y) - \theta^{S_1}(y)|,$$

because then $C = AB$ satisfies the required condition. Since p is differentiable with a derivative that is bounded and bounded away from zero, constant $B = max_{x\in[0,\infty)}|p\prime(x)|$ can be used.

The last step is to show that $A = max_{x\in[1,\overline{S}]}|\frac{1}{q\prime(q^{-1}(x)}|/c$ satisfies the required condition.

There are four cases to consider: $\tilde{J}^{S_2}(y), \tilde{J}^{S_1}(y) \geq c$, $\tilde{J}^{S_2}(y) \geq c > \tilde{J}^{S_1}(y)$, $\tilde{J}^{S_1}(y) \geq c > \tilde{J}^{S_2}(y)$ and $c > \tilde{J}^{S_2}(y), \tilde{J}^{S_1}(y)$. It holds that $\tilde{J}^S$ is bounded from above by $\overline{S}$ and that $|\tilde{J}^{S_2}(y)) -$

$\tilde{J}^{S_1}(y)| \leq ||S_1 - S_2||$. In the first case, it holds that

$$
\begin{aligned}
&|\theta^{S_2}(y) - \theta^{S_1}(y)| = |q^{-1}(c/\tilde{J}^{S_2}(y)) - q^{-1}(c/\tilde{J}^{S_1}(y))| = |\int_{c/\tilde{J}^{S_1}(y)}^{c/\tilde{J}^{S_2}(y)} q^{-1\prime}(x)dx| \\
&\leq max_{x\in[c/\tilde{J}^{S_2}(y), c/\tilde{J}^{S_1}(y)]}|q^{-1\prime}(x)| * |\frac{c}{\tilde{J}^{S_2}(y)} - \frac{c}{\tilde{J}^{S_1}(y)}| \\
&\leq max_{x\in[1,\overline{S}]}|q^{-1\prime}(x)| * |\frac{c}{\tilde{J}^{S_2}(y)} - \frac{c}{\tilde{J}^{S_1}(y)}| \\
&\leq max_{x\in[1,\overline{S}]}|\frac{1}{q\prime(q^{-1}(x)}| * |\frac{c}{\tilde{J}^{S_2}(y)} - \frac{c}{\tilde{J}^{S_1}(y)}| \\
&\leq max_{x\in[1,\overline{S}]}|\frac{1}{q\prime(q^{-1}(x)}| * |(\tilde{J}^{S_1}(y) - \tilde{J}^{S_2}(y))/c| \\
&\leq A||S_1 - S_2||.
\end{aligned}
$$

In the second case, we have that $\theta^{S_1}(y) = 0$, and similar steps as above applied with substitution of 0 for $\theta^{S_1}(y)$ yield

$$
\begin{aligned}
&|\theta^{S_2}(y) - \theta^{S_1}(y)| = |\theta^{S_2}(y) - 0| = |q^{-1}(c/\tilde{J}^{S_2}(y)) - q^{-1}(1)| \\
&\leq max_{x\in[1,\overline{S}]}|\frac{1}{q\prime(q^{-1}(x)}| * |c - \tilde{J}^{S_2}(y))/c| \\
&=\leq max_{x\in[1,\overline{S}]}|\frac{1}{q\prime(q^{-1}(x)}| * (\tilde{J}^{S_2}(y)) - c)/c \\
&=\leq max_{x\in[1,\overline{S}]}|\frac{1}{q\prime(q^{-1}(x)}| * (\tilde{J}^{S_2}(y)) - \tilde{J}^{S_1}(y)))/c \\
&\leq A||S_1 - S_2||.
\end{aligned}
$$

The third case is analogous. Finally, in the fourth case, we have that $|\theta^{S_2}(y) - \theta^{S_1}(y)| = 0$.

In the case (2), when $\tilde{P}^S$ is defined by the equation (2.12), there are five cases to consider: $\tilde{J}^{S_2}(y), \tilde{J}^{S_1}(y) \geq c + ce$, $\tilde{J}^{S_2}(y) \geq c + ce \geq \tilde{J}^{S_1}(y) \geq c$, $c + ce \geq \tilde{J}^{S_2}(y), \tilde{J}^{S_1}(y) \geq c$, $c + ce \geq \tilde{J}^{S_2}(y) \geq c \geq \tilde{J}^{S_1}(y)$ and $c > \tilde{J}^{S_2}(y), \tilde{J}^{S_1}(y)$. In each of these cases, it is easy to find C_i, $i \in \{1, 2, 3, 4, 5\}$, such that $|\tilde{P}^{S_2}(y) - \tilde{P}^{S_2}(y)| \leq C_i||S_2 - S_1||$. The largest of C_i is the desired constant C.

□

Appendix B: Monotone Iteration

To narrow down the set of possible equilibria, I use a method known in numerical functional analysis, discussed in Collatz (1966). Consider a functional operator $\mathcal{T} : \mathcal{S} \to \mathcal{S}$, where $\mathcal{S}$ is a space of real-valued functions from X to a compact set, which contains bounds $\underline{S}, \ \overline{S} \in \mathcal{S}$ such that $\forall_{x \in X} \ \underline{S}(x) \leq S(x) \leq \overline{S}(x)$.

Suppose that $\mathcal{T}$ can be decomposed into an increasing (monotone) operator $\mathcal{T}^1$ and a decreasing (antitone) operator $\mathcal{T}^2$: there are $\mathcal{T}^1, \mathcal{T}^2 : \mathcal{S} \to \mathcal{S}$ such that $\forall_{x \in X} \ \mathcal{T}(x) = \mathcal{T}^1(x) + \mathcal{T}^2(x)$ and such that if $\forall_{x \in X} \ S_1(x) \leq S_2(x)$ for $S_1, S_2 \in \mathcal{T}$, then $\forall_{x \in X} \ \mathcal{T}^1 S_1(x) \leq \mathcal{T}^1 S_1(x)$ and $\mathcal{T}^1 S_1(x) \geq \mathcal{T}^1 S_1(x)$.

We can define two sequences of functions, $\underline{S}_n$ and $\overline{S}_n$, where the nitial elements are $\underline{S}_0 = \underline{S}$ and $\overline{S}_0 = \overline{S}$. The subsequent elements are defined as

$$\underline{S}_{n+1} = \mathcal{T}^1 \underline{S}_n + \mathcal{T}^2 \overline{S}_n$$

and

$$\overline{S}_{n+1} = \mathcal{T}^1 \overline{S}_n + \mathcal{T}^2 \underline{S}_n.$$

Lemma 2.5.2. *The inequalities*

$$\underline{S}_0(x) \leq \underline{S}_1(x) \leq ... \leq \underline{S}_n(x) \leq \overline{S}_n(x) \leq ... \leq \overline{S}_1(x) \leq \overline{S}_0(x)$$

hold for all $n \in \mathbb{N}$ *and* $x \in X$.

Proof. By induction. The inequality $\underline{S}_0(x) \leq \overline{S}_0(x)$ holds by assumption. From $\underline{S}_n(x) \leq \overline{S}_n(x)$ it follows that

$$\underline{S}_{n+1}(x) = \mathcal{T}^1 \underline{S}_n(x) + \mathcal{T}^2 \overline{S}_n(x) \leq \mathcal{T}^1 \overline{S}_n(x) + \mathcal{T}^2 \underline{S}_n(x) = \overline{S}_{n+1}(x)$$

from the monotone properties of $\mathcal{T}^1, \mathcal{T}^2$. □

Lemma 2.5.3. *For any fixed point S^* of the operator $\mathcal{T}$ and any $n \in \mathbb{N}$, the inequalities*

$$\underline{S}_n(x) \leq S^*(x) \leq \overline{S}_n(x)$$

hold for all $x \in X$.

Proof. By induction. The inequality $\underline{S}(x) = \underline{S}_0(x) \leq S^*(x) \leq \overline{S}_0(x) = \overline{S}(x)$ holds by assumption. From $\underline{S}_n(x) \leq S^*(x) \leq \overline{S}_n(x)$, it follows that

$$\underline{S}_{n+1}(x) = \mathcal{T}^1\underline{S}_n(x) + \mathcal{T}^2\overline{S}_n(x) \leq S^*(x) \leq \mathcal{T}^1\overline{S}_n(x) + \mathcal{T}^2\underline{S}_n(x) = \overline{S}_{n+1}(x)$$

from the monotone properties of $\mathcal{T}^1, \mathcal{T}^2$.

□

From the first lemma, it follows that, for all $x \in X$, an ascending and bounded from above sequence $\overline{S}_n(x)$ and a descending and bounded from below sequence $\underline{S}_n(x)$ have limits, $\underline{\underline{S}}(x)$ and $\overline{\overline{S}}(x)$, since functions from the space $\mathcal{S}$ have values in a compact set. Consequently, it is possible to numerically narrow down the set of fixed points of $\mathcal{T}$, by constructing $\underline{S}_n$ and $\overline{S}_n$ and finding their limits, which is done by iteration.

Both the original operator $\mathcal{T}$ and the proxy operator $\tilde{\mathcal{T}}$ are decomposable into monotone and antitone parts. For the operator $\mathcal{T}$, these parts are $\mathcal{T}^1$ and $\mathcal{T}^2$ such that

$$(\mathcal{T}^1 S)(y, z) = r(y, z) - b + \beta\mathbb{E}\Big[(1-\delta)\mathbb{1}\{S(\hat{y}, z) \geq 0\}S(\hat{y}, z)\Big]$$

and

$$(\mathcal{T}^2 S)(y, z) = -\beta\mathbb{E}\Big[P^S(\hat{y})\int \mathbb{1}\{(1-\tau)S(\hat{y}, \hat{z}) \geq h\}\tau S(\hat{y}, \hat{z})dF_Z(\hat{z})\Big].$$

For the operator $\tilde{\mathcal{T}}$, these parts are $\tilde{\mathcal{T}}^1$ and $\tilde{\mathcal{T}}^2$ such that

$$(\tilde{\mathcal{T}}^1 S)(y, z) = r(y, z) - b + \beta\mathbb{E}\Big[(1-\delta)\mathbb{1}\{S(\hat{y}, z) \geq 0\}S(\hat{y}, z)\Big]$$

and

$$(\tilde{\mathcal{T}}^2 S)(y, z) = -\beta \mathbb{E}\Big[\tilde{P}^S(\hat{y}) \int a^S(\hat{y}, \hat{z}) \tau S(\hat{y}, \hat{z}) dF_Z(\hat{z})\Big].$$

Chapter 3

Dynamics of Wages Around Job Transitions

3.1 Introduction

Job-to-job transitions are a widespread feature of the labor market. A fraction of job-to-job transitions associated with a wage cut is surprisingly large, ranging from one fifth to more than one third. In the German dataset used in this paper, the fraction of such transitions is 31%.[1] This phenomenon is a challenge for labor market models.

The goal is to empirically investigate the previously proposed explanations, using administrative German microdata that provide information on whole employment history of a large sample of workers recorded at daily frequency. I compare the evolution of wages for continuously employed workers, workers making a job-to-job (EE) transition, workers making a job-unemployment-job (EUE) transition, and workers who experience separation followed by a longer period of non-employment.[2]

[1]Jolivet et al. (2006) use the data from the ECHP for Europe and the PSID for the US, concluding that in the 1990s the fraction of such transition ranged from 20% in Belgium to 36% in Germany, and was 23% in the US. Tjaden and Wellschmied (2014) find that the fraction to 34% in the PSID data from the 1990s, with the average wage cut of 20%. Other papers find similar values for the fraction of wage-decreasing wage cuts.

[2]Workers are classified as making an EE transition if they are observed leaving a job and starting another without registering as unemployed within a short period, which is 0 to 9 days for most of the paper. Workers who register as

Wage changes associated with transitions are compared to wage changes within employment spells. I find that wage changes associated with EE transitions and within-spell changes show similar patterns across time and demographic groups. The fraction of wage cuts for EE transitions, 31%, is not drastically higher than for within-spell changes, 26%. In contrast, the fraction of cuts is 47% for EUE transitions.

One group of explanations wage cuts associated with EE transitions posits that workers move to a new job to escape a deteriorating match or to avoid an even worse situation in the future. In the model of Moscarini (2005), continuous learning about initially unknown match quality can lead to gradual deterioration of wages and eventual separation. In Nagypal (2005a), large shocks can lower the value of a job, leading to an immediate separation or at least increased likelihood of a smaller shock triggering separation. Alternatively, a reallocation shock, nicknamed ”Godfather shock,” can force workers to choose between a random outside offer and unemployment, as in Jolivet, Postel-Vinay and Robin (2006). Unlike a pure reallocation shock, a worsening job situation could manifest as lowering of wages or wage growth.

Examining the evolution of wages before separation, I find that wages deteriorate in the months leading to separation, for all types of separations, even job-to-job transitions. The wage deterioration manifests in the year preceding transition as slower wage growth and lowering of real wages conditioned on workers' characteristics. Wage growth for workers who avoid separation is 3%. Before EE and EUE transitions, yearly wage growth is lower by half and two-thirds, respectively. For other separations, wage growth is slightly negative. Real wages adjusted for workers' characteristics are lowered by 0.6% a year before separation, and lowered by 2-3% in the last pre-separation quarter. For EE transitions, wages are lowered by 0.5% half a year before separation, and by

unemployed before or after separation and start a new job within a period of the same length are classified as making an EUE transition.

around 1.5% immediately before separation. Other types of separations are preceded by more wage deterioration. The observed wage deterioration supports the notion some of separations are preceded by a worsening job situation, even for job-to-job transitions.

Another group of explanations proposes that workers move to a lower-paying job in the expectation of obtaining higher wages in the future. This motive arises if firms offer an increasing wage-tenure profile, as in Coles and Burdett (2010) extension of the Burdett-Mortensen wage posting model; if some firms offer attractive opportunities for accumulation of firm-specific or general human capital; and in the Bertrand competition framework introduced in Robin and Postel-Vinay (2002). In this framework, workers have no bargaining power, receiving take-it-or-leave-it offers from firms. Wage growth results from the Bertrand competition in which firms engage when a worker receives an outside offer, within the limit dictated by productivity in the current job. A worker might make a job-to-job transition because of the option value of working for a more productive firm with higher wage ceiling, despite the initial wage being lower.

Examining the evolution of wages after accession, I find that after EE transitions wages grow faster for workers who accept an initial wage cut. Wage growth is negatively correlated with the initial wage for all workers, and positively with previous wage for workers who move between jobs. However, the finding on wage growth after EE transitions is robust to controlling for initial and previous wages. This effect is not present for EUE transitions.

The findings of the paper suggest that both motivations for a job-to-job transition accompanied by a wage cut are plausible. The observed wage deterioration indicates that some of separations are preceded by a worsening job situation, even for job-to-job transitions. The positive correlation between wage growth and the initial wage cut for job-to-job transitions suggests that at least some of workers might accept lower initial wages in the exchange for higher future wage growth.

3.2 Previous Empirical Findings

Job-to-job transitions accompanied by a wage cut are a pervasive phenomenon in the labor markets. Jolivet, Postel-Vinay and Robin (2006) use panels of worker data for 10 European countries and the US, the European Community Household Panel and the Panel Study of Income Dynamics for the mid-1990s. They find that the fraction of job-to-job transitions associated with a wage cut ranges from around 18% in Portugal to 36% in Germany. The wage cuts exceed 10% for 10% to 20% of transitions for most of the considered countries, with 29% in France, and exceed 20% for between 7% and 20% of transitions. Their explanation for these transition is the presence of reallocation shocks, which force workers to choose between a random outside offer and unemployment.

Lopes de Melo (2007) looks at wage dynamics using the 1996 panel of the Survey of Income Program and Participation. He finds a significant amount of wage cuts and more wage movements, both downward and upward, in job-to-job transitions than for job stayers, with higher variance. Wage growth is compared for workers that undertake a job-to-job transition with a wage decrease in the first observed year and workers who keep their job initially, but experience a transition afterwards. Wage growth is higher for the stayers in the low education group, but appears to be lower in the high education group, supporting the notion that a wage cut might be accepted in the expectation of higher future wages. The caveat is, however, a small sample size: the 4-year wage growth is examined for 134 job-to-job transitions with wage cuts in the low education group and 34 in the high education group.

Tjaden and Wellschmied (2014) find that one third of job-to-job transitions are associated with a wage cut in data from the Survey of Income and Program Participation for the 1993-1995 and 1996-1999. Additionally, workers who experience a wage cut are more likely to change jobs again.

Canon and Pavan (2014) investigate what happens to wages of workers before they make a job-to-job transition. They use two measures of compensation from the National Longitudinal Survey of Youth datasets 1979: usual wages earned and total labor earnings during the previous year. They find evidence that wages decrease before a job-to-job transition, and argue that experiencing a negative productivity and wage shock are more likely to change jobs. Additionally, they use the 1996 panel of the Survey of Income and Program Participation to investigate dynamics of monthly labor income. They use dummies for future and past labor market transitions within the next 6 months and the previous 6 months. Workers who experience a transition in the recent past or the imminent future experience a within-job wage growth 1% lower than stayers, in both cases.

Additional explanations for job-to-job transitions accompanied by wage cuts were investigated. Workers might make a transition for non-pecuniary reasons, moving to a job that they value more despite worse pay. Fujita (2010) finds that in the UK workers who are unsatisfied with non-pecuniary characteristics of their job are roughly half of workers who search on the job and give job dissatisfaction as a reason. The workers unsatisfied for non-pecuniary reasons obtain on average lower wages conditional on moving than workers who search on the job due to low pay. Hall and Mueller (2018) find that non-wage value of a job plays an important role for the job-acceptance decisions of unemployed job seekers in the US. Sorkin (2018) finds evidence for movement to lower-paying firms suggestive of compensating differentials in US administrative data. Additionally, the observed wage cuts might be an artifact of measurement error, which was investigated in Canon and Pavan (2014).

3.3 Data

I use German administrative microdata, the Sample of Integrated Labour Market Biographies for 1975-2010, which is 2% sample of German workers[3] provided by the Research Data Centre of the Federal Employment Agency at the Institute for Employment Research. A detailed description of the dataset is provided in vom Berge, Koenig and Seth (2013).

For each worker, I have information on all employment spells covered by social security between 1975 and 2010: an establishment identifier, sex, education, location, working hours (full-time or part-time), employment status (indicators for special status such as traineeship, partial retirement and others), daily earnings, and other information. Job tenure can be precisely calculated. Every time conditions of employment change, a notification has to be submitted to the social security system. Consequently, workers are observed at effectively daily frequency.

I restrict the sample to men between 25 and 54 years of age. The restriction is adopted for comparability with earlier studies. The lower bound of 25 years is customary, the upper bound of 54 years is lower than the usual bound of 60 years, in this case chosen to avoid issues raised by early retirement. I further restrict the sample to employment spells in which a worker is employed continuously (with no gaps), as a full-time non-trainee, and without any parallel employment. Such spells are more than a half of all employment spells. To calculate wage changes associated with movement to a different job, I restrict the sample to movement to jobs in which a worker is initially employed as a full-time non-trainee, and without any parallel employment. To investigate wage dynamics after movement to a different job, I restrict the sample to movement from jobs in which a worker was employed at the end of a spell as a full-time non-trainee, and without any parallel employment. The observations with daily earnings above the legally mandated contribution as-

[3]Individuals appear in underlying data if at least once in the 1975-2010 period they are employees covered by the social security system or register as unemployed, job seekers or benefit recipients.

sessment ceiling (Beitragsbemessungsgrenze) are top-coded. Wages are defined as nominal daily earnings of full-time workers. I calculate wage changes within and between employment spells only for uncensored observations.

3.4 Empirical Results

This section starts with statistics on wage changes within employment spells, which serve as a benchmark for wage changes associated with transitions. Then, dynamics of wages before separations and after accessions are examined.

3.4.1 Wage Changes Within Employment Spells

To provide a benchmark for wage changes experienced by workers moving between jobs, I establish the properties of wage changes within employment spells. The fraction of wage cuts is 26% for all workers and stable across age groups, but much lower, 15%, for university-educated workers than for the rest. Over the considered period, the fraction of wage cuts shows an upward trend. The mean and dispersion of wage changes is higher for younger and less educated workers. Overall, the mean wage change is 3%, with the standard deviation of 0.14. The mean wage decrease is -8.7% and the mean wage increase is 7.1%. The results are summarized in Table 3.1.

For workers aged 25-34, 35-44, 45-54, the fraction of cuts is similar, close to 26%. Wage changes are on average larger and more dispersed for the youngest workers. The results are summarized in Table 3.2.

When workers are divided into groups with and without university education, the fraction of cuts turns out to be much lower, 15%, in the high-education group, than in the low-education group, 28%. For the high-education group, wages changes are slightly larger with smaller dispersion. The results are summarized in Table 3.3.

Since the sample covers 20 years, the properties of wage changes might have changed over time. The statistics computed for each year separately turn out to be relatively stable over time, excluding the first five years of the considered period. However, the fraction of cuts was higher in the 2000s than the 1990s, 28% to 22%. In years 1990-1994, the fraction of cuts was noticeably lower, 13%-24% in a year, than in 1995-2009, when it ranged from 24% to 34%. The mean and dispersion of wage changes was slightly lower the later decade. The mean of wage changes in 1990-1994 ranged from 3.6% to 6%, in 1995-2009, from 1.3% to 3.7%. Unsurprisingly, the mean wage change was the lowest in 2008, with the fraction of decreases close to the maximum observed in the whole period. The results are summarized in Table 3.24.

The wage changes are not distributed uniformly over a year. More than 40% of all wage changes observed in a year happen in December. The December wage changes have slightly higher standard deviation and fraction of wage decreases. However, the differences are small. The results are summarized in Table 3.25.

Table 3.1: Wage Changes for Job Stayers

Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1924654	0.0302	0.14	25.88	-0.0873	0.0713

Notes: Mean in log points, fraction in percentage points.

Table 3.2: Wage Changes for Job Stayers, by Age Group

Age	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
25-34	647838	0.0405	0.16	25.88	-0.1001	0.0896
35-44	756636	0.0268	0.13	25.74	-0.0826	0.0647
45-54	520180	0.0224	0.12	26.08	-0.0783	0.0579

Notes: Mean in log points, fraction in percentage points.

Table 3.3: Wage Changes for Job Stayers, by Education

University	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
No	11560419	0.0286	0.14	28.36	-0.0888	0.0750
Yes	364235	0.0374	0.12	15.27	-0.0750	0.0576

Notes: Mean in log points, fraction in percentage points.

3.4.2 Wage Changes for Transitions

For transitions, the fraction of wage cuts is 31% for EE transitions and 47% for EUE transitions. The fraction of wage cuts for EE transitions is not drastically higher than 26% found for within-spell wage changes. The mean wage change for EE transitions, 5.8%, is almost twice the mean for within-spell changes, and dispersion is correspondingly higher. For EUE transition, the mean wage change is 0.1% and dispersion is much higher than for EE transitions and job stayers. The results are summarized in Table 3.4.

Across age and education groups, wage changes associated with EE transitions show similar patterns to within-spell changes. The fraction of cuts is similar for workers aged 25-34, 35-44, 45-54, but higher for low-education workers, 33%, than for high-education workers, 26%. The mean and dispersion of changes are larger for younger workers, the mean is slightly, and dispersion noticeably, larger for low-education than for high-education workers. The results are summarized in Tables 3.5 and 3.6.

As for within-spell wage changes, the fraction of cuts associated with EE transitions shows an upward trend in 1990-2009, while the mean and dispersion were relatively stable. In contrast to within-spell changes, the fraction of cuts for EE transitions, was below the mean, 29%, in 2008, but reached the maximum in the sample, 36.6%, in 2009, with the smallest observed mean. The results are summarized in Table 3.26.

EE transitions are less concentrated in December than within-spell wage changes, with 26% on average happening at the end of year. The mean and dispersion of wage changes, and the fraction of wage cuts, are higher in the January-November period than in December An exception was 2009, when the mean change in the first 11 months was roughly equal to the mean for December, with the fraction of cuts reaching the maximum in the sample. The results are summarized in Table 3.27.

Figures 3.1 and 3.2 show the distributions of wage changes within spells and for EE and EUE transitions.

Figure 3.1: Wage Changes

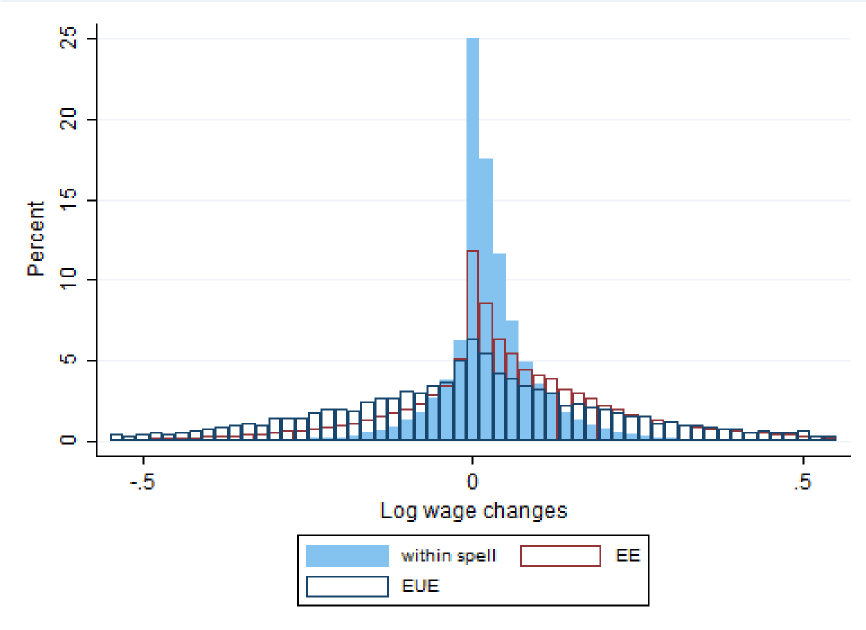

Figure 3.2: Wage Changes in December

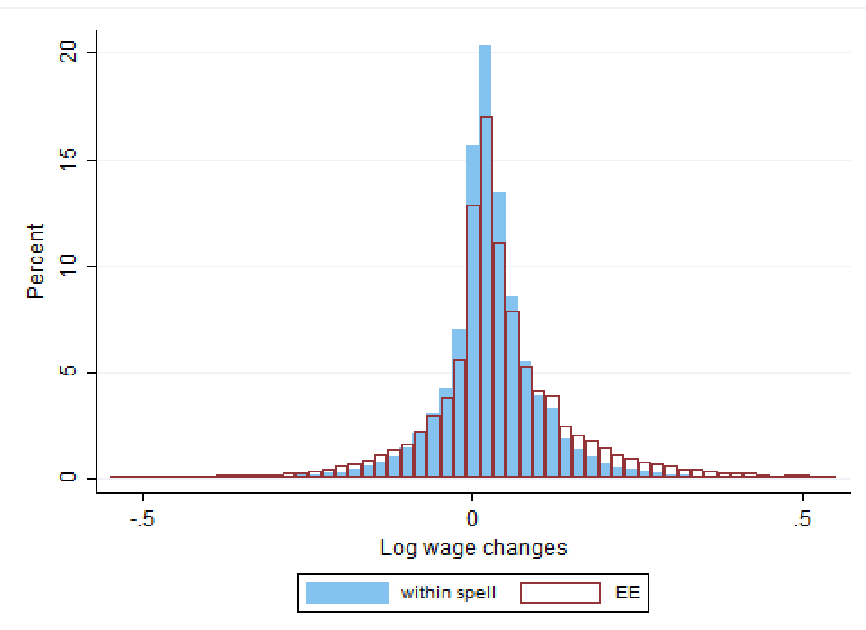

Table 3.4: Wage Changes for EE and EUE Transitions

Type	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
EE	261186	0.0578	0.26	31.36	-0.1622	0.1583
EUE	17584	0.0008	0.35	47.09	-0.2344	0.2101

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points, fraction in percentage points.

Table 3.5: Wage Changes for EE Transitions, by Age

Age	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
25-34	109738	0.0770	0.28	30.68	-0.1798	0.1906
35-44	94896	0.0485	0.24	31.64	-0.1530	0.1418
45-54	56552	0.0361	0.23	32.22	-0.1450	0.1222

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points, fraction in percentage points.

Table 3.6: Wage Changes for EE Transitions, by Education

University	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
No	215539	0.0588	0.27	32.60	-0.1716	0.1702
Yes	45647	0.0532	0.20	25.51	-0.1057	0.1076

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points, fraction in percentage points.

3.4.3 Pre-Separation Wage Dynamics

The evolution of wages before separation is investigated to examine whether movement between jobs, in particular job-to-job transitions, are induced by worsening of an existing match. I find that wages deteriorate in the months leading to separation, for all types of separations. The deterioration is visible in lowered wage growth in the year preceding separation, and as lowered wage levels. For EE transitions, the deterioration is weaker, but still present.

The yearly mean wage growth is 3% for workers who avoid separation, 1.8% for workers who make an EE transition, 0.9% for workers who make an EUE transition, and -0.1 for workers who undergo separation of different type, as shown in Table 3.7.

To check if differences in wage growth are not driven by composition of workers' groups, I estimate the equation

$$\Delta log\, w_{it} = \alpha_{it}^{EE} + \alpha_{it}^{EUE} + \alpha_{it}^{S} + \beta \boldsymbol{x}_{it} + \epsilon_{it} \tag{3.1}$$

where $\Delta log\, w_{it}$ is the year-on-year difference in log wages for worker i in month t, α_{it}^{EE}, α_{it}^{EUE}, α_{it}^{S} are fixed effects for undergoing an EE transition, an EUE transition, or other separation, respectively. The vector of controls, $\boldsymbol{x}_{it}$, contains tenure, an education-specific quadratic polynomial in age, and federal state and month fixed effects. The results from the regression, shown in Table 3.8, indicate that the differences in wage growth are robust to controlling for compositional effects.

The deterioration in wages is stronger immediately before separation. To examine the evolution of wages in the year before separation, I estimate the equation

$$log\, w_{it} = \sum_{j=1}^{J} \sum_{k=-12}^{0} \delta_{it}^{j,k} + \beta \boldsymbol{y}_{it} + \epsilon_{it} \tag{3.2}$$

where w_{it} is wage for worker i in month t, $\delta_{it}^{j,k}$ are fixed effect for months in which worker i is k months before separation of type j. The vector of controls, $\boldsymbol{y}_{it}$, contains a quadratic polynomial in tenure, an education-specific cubic polynomial in age, and federal state and month fixed effects, and a match fixed effect specific for a worker-firm pair. Equation 3.2 conditions wages on workers' characteristics, average wages for a worker-firm pair and the overall wage level. Consequently, the fixed effects for pre-separation months capture deterioration in expected real wages.

The results from the estimation of Equation 3.2 without differentiating between separations, shown in column (1) of Table 3.9, indicate that on average wages are the lower, the closer is separation, with deterioration by 0.6% a year before separation, and by 2-3% in the last pre-separation quarter. The results from the estimation of Equation 3.2 with separations divided between EE transitions, EUE transitions and other separations, shown in columns (2)-(4) of Table 3.9, indicate that for EE transitions the deterioration starts later and is weaker than for other transitions. The differences between EUE transitions and remaining separations are small.

Wage dynamics before job-to-job transitions with a gap of 0-9 days are markedly different than for other separations. Additional regressions estimated, but not included, for workers undergoing movement between jobs with and without unemployment registration with an employment gap of 10-31 and 32-93 days show that pre-separation wage dynamics for these group are similar to wage dynamics preceding EUE with a gap of 0-9 days.

Table 3.7: Wage Growth Pre-Separation

Status	N	Mean	St. Dev.
Stayers	19229442	0.0302	0.0952
EE	157582	0.0177	0.1345
EUE	9181	0.0089	0.1658
Other	145317	-0.0007	0.1992

Table 3.8: Pre-Separation Wage Growth

$\hat{\alpha}^{EE}$	$\hat{\alpha}^{EUE}$	$\hat{\alpha}^{S}$
-0.0169***	-0.0196***	-0.0352***
(0.0018)	(0.0022)	(0.0016)

Notes:* $p < .1$, ** $p < .05$, *** $p < .01$; month-clustered standard errors in parentheses; 18908000 monthly observations for 424238 worker-firm pairs, 265093 workers, 237397 firms, 149306 EE transitions, 8546 EUE transitions and 139271 remaining separations.

Table 3.9: Pre-Separation Wage Dynamics

	(1)	(2)	(3)	(4)
Month	All Separations	EE Transitions	EUE Transitions	Other Separations
0	-0.0292***	-0.0155***	-0.0349***	-0.0436***
	(0.0015)	(0.0014)	(0.0017)	(0.0015)
1	-0.0253***	-0.0135***	-0.0324***	-0.0383***
	(0.0012)	(0.0013)	(0.0015)	(0.0012)
2	-0.0224***	-0.0121***	-0.0310***	-0.0343***
	(0.0010)	(0.0012)	(0.0014)	(0.0010)
3	-0.0189***	-0.0092***	-0.0280***	-0.0302***
	(0.0009)	(0.0010)	(0.0011)	(0.0009)
4	-0.0169***	-0.0080***	-0.0262***	-0.0274***
	(0.0008)	(0.0009)	(0.0011)	(0.0008)
5	-0.0152***	-0.0068***	-0.0245***	-0.0251***
	(0.0007)	(0.0009)	(0.0010)	(0.0008)
6	-0.0129***	-0.0050***	-0.0230***	-0.0223***
	(0.0007)	(0.0008)	(0.0010)	(0.0007)
7	-0.0113***	-0.0039***	-0.0213***	-0.0202***
	(0.0006)	(0.0007)	(0.0011)	(0.0007)
8	-0.0096***	-0.0026***	-0.0194***	-0.0180***
	(0.0006)	(0.0007)	(0.0010)	(0.0007)
9	-0.0075***	-0.0009	-0.0181***	-0.0154***
	(0.0005)	(0.0006)	(0.0009)	(0.0006)
10	-0.0060***	0.0003	-0.0172***	-0.0134***
	(0.0004)	(0.0006)	(0.0009)	(0.0006)
11	-0.0052***	0.0009	-0.0174***	-0.0121***
	(0.0004)	(0.0006)	(0.0009)	(0.0005)
12	-0.0058***	-0.0015***	-0.0166***	-0.0104***
	(0.0004)	(0.0005)	(0.0009)	(0.0004)

Notes:* $p < .1$, ** $p < .05$, *** $p < .01$; month-clustered standard errors in parentheses; 25891874 monthly observations for 790450 worker-firm pairs, 341403 workers, 414361 firms, with 259029 EE transitions, 18667 EUE transitions and 512754 remaining separations. The estimates of fixed effects for months pre-separation, from estimation for pooled separations in column (1) and for separations divided into 3 groups in columns (2)-(4).

3.4.4 Wage Dynamics After Transitions

The evolution of wages after movement between jobs is investigated to examine the plausibility of the hypothesis that job-to-job transitions with wage cuts are undertaken in the expectation of obtaining higher wages in the future. I find that for EE transitions wage growth is higher for transitions associated with a wage cut.

Wages of workers whose wages initially decreased grow on average faster, for both EE and EUE transitions, as summarized in Table 3.10. In general, wage growth is negatively correlated with the initial wage, and, for workers who move between jobs, positively with previous wage. Consequently, higher wage growth for transitions associated with a cut is expected. To check if the relationship between wage cuts and subsequent growth is not fully driven by the initial and preceding wages, I estimate the equation

$$\Delta^k log\, w_{it} = \rho^k_{it} + \beta^k \boldsymbol{z}_{it} + \epsilon^k_{it} \tag{3.3}$$

where $\Delta^k log\, w_{it}$ is the difference of log wages of worker i in month t and month $t-k$, and ρ^k_{it} is a fixed effect for starting a job with lower wage than in the previous job. The vector of controls, $\boldsymbol{z}_{it}$, contains tenure, an education-specific quadratic polynomial in age, and federal state and month fixed effects, and initial and previous wages. The estimates of ρ^k_{it} from estimating Equation 3.3 separetely for workers making EE or EUE transitions and for k-month wage growth, where $k \in \{3, 6, 12, 18, 24, 36, 48, 60\}$, are shown in Table 3.11.

The results for EE transitions indicate that wages of workers who accepted a wage cut grow faster. After 3 months, the estimated difference in growth is 0.5%, with the raw difference of 1.9% and the mean growth of 0.7% for all EE transitions; after 5 years, the difference in growth is 1.08%, with the raw difference of 5.1% and the mean growth of 16.9%. The effect persists over time, but becomes much smaller relative to overall wage growth. When the same equation is estimated for

EUE transitions, the wage cut fixed effects are not significant.

Table 3.10: Wage Growth After Transitions

Type	Month	3	6	12	18	24	36	48	60
EE	N	235177	206309	162227	137252	112942	83909	64595	50991
	Mean	0.7	1.5	4.1	5.8	7.9	11.2	13.9	16.9
EE ↑	N	155999	139790	111813	95531	78938	59133	46028	36419
	Mean	0.1	0.5	2.7	4.3	6.4	9.5	12.3	15.2
EE ↓	N	64677	54137	41130	34031	28052	20501	15600	12238
	Mean	2.0	3.7	6.6	8.6	10.7	14.1	17.0	20.1
EUE	N	13509	10225	7049	5410	4188	2795	1917	1356
	Mean	1.2	2.6	5.2	7.3	9.4	13.1	16.5	19.0
EUE ↑	N	6685	5229	3746	2903	2242	1490	1018	729
	Mean	0.7	1.7	3.8	5.6	7.7	10.7	14.1	15.7
EUE ↓	N	5709	4129	2698	2055	1589	1070	748	521
	Mean	1.8	3.8	6.7	9.2	11.0	15.0	18.3	22.1

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points. The signs ↑ and ↓ indicate transitions associated with wage increases and decreases.

Table 3.11: Wage Growth After Transitions

	EE		EUE	
Month	$\hat{\rho}$	N	$\hat{\rho}$	N
3	0.0052***	199737	0.0017	11536
	(0.0007)		(0.0023)	
6	0.0076***	176886	0.0011	8814
	(0.0015)		(0.0048)	
12	0.0072***	138571	0.0018	6046
	(0.0024)		(0.0068)	
18	0.0094***	118262	0.0077	4663
	(0.0024)		(0.0081)	
24	0.0097***	97014	0.0080	3575
	(0.0028)		(0.0103)	
36	0.0111***	72531	0.0101	2395
	(0.0036)		(0.0172)	
48	0.0128***	56215	0.0044	1647
	(0.0045)		(0.0214)	
60	0.0108*	44520	0.0305	1155
	(0.0057)		(0.0262)	

Notes:* p$<$ .1, ** p$<$.05, *** p$<$.01; standard errors in parentheses are clustered by intial month. The estimates of the coeficient on the indicator for a wage-decreasing transition, separately for $3, 6, 12, 18, 24, 36, 48, 60$ months after a transition and EE and EUE transitions.

3.5 Conclusions

I examine plausibility of two leading explanations for job-to-job transitions associated with a wage cut by looking at the evolution of wages before and after transition. I find that wages deteriorate in months leading to transition, which supports the notion that workers move between jobs to escape a deteriorating match. However, wages grow faster for workers who accepted wage cuts, at least after job-to-job transitions. Wage growth after movement between jobs associated with even short unemployment is not positively associated with a wage cut.

Taken together, the findings suggest that both transitions induced by worsening of an existing match, and acceptance of lower initial wage in the exchange for higher future wage growth are present in the labor market.

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Appendix A: Samples

Table 3.12: Sample for Job Stayers

Spells	Workers	Firms	Changes
864604	349879	451796	1924654

Table 3.13: Sample for Job Stayers, by Age Group

Age	Spells	Workers	Firms	Changes
25-34	423157	207979	265025	647838
35-44	353753	190797	226168	756636
45-54	232719	144893	154581	520180

Table 3.14: Sample for Job Stayers, by Education

University	Spells	Workers	Firms	Changes
No	742975	303986	412875	1560419
Yes	123672	59184	73441	364235

Table 3.15: Sample for Job Stayers, by Year

Year	Spells	Workers	Firms	Changes
1990	109557	97969	66640	79799
1991	116279	104876	71270	84058
1992	154365	137149	94444	104759
1993	148404	133155	94775	98293
1994	145565	130626	95200	97999
1995	142544	128148	94250	94452
1996	140443	126828	93163	92769
1997	138613	125221	92749	91431
1998	138359	124929	92299	93479
1999	141756	126688	94391	96815
2000	145365	128756	95755	98362
2001	144415	129120	94594	101904
2002	138223	125810	90384	99733
2003	132571	122165	86440	99809
2004	129430	119752	83794	95265
2005	126958	117607	81802	92321
2006	130948	120106	83236	87085
2007	137451	124400	86697	106653
2008	140696	127759	88312	105361
2009	139163	127665	68064	104307

Table 3.16: Sample for Job Stayers in the 1990s, by Period

Period	Spells	Workers	Firms	Changes
1-11.1990	108392	97332	65961	754773
12.1990	86297	86249	51582	77595
1-11.1991	115257	104322	70621	809611
12.1991	92093	92053	55531	82212
1-11.1992	152955	136526	93534	995873
12.1992	118114	118036	72544	101488
1-11.1993	147022	132537	93867	942189
12.1993	113984	113903	72635	95288
1-11.1994	144013	129907	94168	942265
12.1994	113408	113291	73960	95732
1-11.1995	141071	127422	93341	902713
12.1995	110858	110771	72923	91804
1-11.1996	139125	126175	92918	893365
12.1996	108968	108898	72441	90628
1-11.1997	137106	124500	91853	867614
12.1997	107432	107364	71793	88738
1-11.1998	136796	124127	91343	879824
12.1998	108278	108192	72217	90880
1-11.1999	140160	125922	93398	886092
12.1999	109925	109827	73530	92232

Table 3.17: Sample for Job Stayers in the 2000s, by Period

Period	Spells	Workers	Firms	Changes
1-11.2000	143575	127964	94714	909889
12.2000	111731	111627	73874	94829
1-11.2001	142996	128496	93736	918378
12.2001	111326	111244	72972	94010
1-11.2002	136965	125240	89592	908601
12.2002	108538	108468	70659	91622
1-11.2003	131365	121569	85713	888462
12.2003	106666	106603	69203	89448
1-11.2004	128240	119156	83048	874607
12.2004	105020	104969	67821	88326
1-11.2005	125682	116978	81032	850271
12.2005	105051	104985	67476	86984
1-11.2006	129561	119368	82432	776849
12.2006	108380	108298	69380	81453
1-11.2007	136032	123723	85892	936401
12.2007	112095	112017	71422	97138
1-11.2008	139421	127144	87539	968412
12.2008	115300	115239	73004	100112
1-11.2009	137857	127016	87283	953449
12.2009	115046	114969	73289	98094

Table 3.18: Sample for Separations

Spells	Workers	Firms	EE	EUE	Other
757159	320122	412558	271548	19318	466293

Table 3.19: Sample for Separations, by Age

Age	Spells	Workers	Firms	EE
25-34	318634	156033	217089	113941
35-44	246446	128996	176252	97579
45-54	148994	86425	111079	58043

Table 3.20: Sample for Separations, by Education

University	Spells	Workers	Firms	EE
No	659341	279922	377604	224103
Yes	97818	49823	62090	47445

Table 3.21: Sample for Separations, by Year

Year	Spells	Workers	Firms	EE
1990	30378	25710	25269	11876
1991	31924	27609	26616	11973
1992	47956	41950	37092	19109
1993	47038	41432	36944	17067
1994	45284	39690	36316	16259
1995	45224	39803	35755	17203
1996	43079	37878	34901	14486
1997	42098	37061	34369	13657
1998	40661	36141	33352	14440
1999	41438	36406	34046	15501
2000	43417	37938	35434	17561
2001	42637	37416	34991	16096
2002	38567	34203	31577	13277
2003	33602	30141	27671	10501
2004	31617	28538	25984	9667
2005	28573	25689	23552	8846
2006	28954	25858	23319	10412
2007	31322	27720	25160	12402
2008	31899	28005	25730	11764
2009	31491	27919	25359	9451

Table 3.22: Sample for Separations in the 1990s, by Period

Period	Spells	Workers	Firms	EE
1-11.1990	24985	21135	21399	9279
12.1990	5393	5386	4670	2597
1-11.1991	26177	22650	22547	9231
12.1991	5747	5744	4952	2742
1-11.1992	38279	33551	31067	14230
12.1992	9677	9667	7489	4879
1-11.1993	37001	32644	30538	12222
12.1993	10037	10031	7732	4845
1-11.1994	34921	30677	29404	11690
12.1994	10363	10341	8252	4569
1-11.1995	33784	29622	28857	11512
12.1995	11440	11431	8164	5691
1-11.1996	33842	29860	28853	10164
12.1996	9237	9231	7149	4322
1-11.1997	33079	29211	28130	9731
12.1997	9019	9011	7293	3926
1-11.1998	31765	28355	27126	10363
12.1998	8896	8888	7257	4077
1-11.1999	33461	29621	28229	11723
12.1999	7977	7967	6894	3778

Table 3.23: Sample for Separations in the 2000s, by Period

Period	Spells	Workers	Firms	EE
1-11.2000	35076	30916	29552	13245
12.2000	8341	8332	6979	4316
1-11.2001	34358	30343	29121	12031
12.2001	8279	8269	6909	4065
1-11.2002	30958	27641	26238	9568
12.2002	7609	7600	6188	3709
1-11.2003	26993	24341	23006	7561
12.2003	6609	6606	5467	2940
1-11.2004	25234	22888	21276	6948
12.2004	6383	6376	5448	2719
1-11.2005	22884	20682	19339	6512
12.2005	5689	5678	4906	2334
1-11.2006	23381	21048	19265	7783
12.2006	5573	5569	4793	2629
1-11.2007	26040	23284	21269	9810
12.2007	5282	5274	4669	2592
1-11.2008	26157	23175	21653	9342
12.2008	5742	5733	4967	2422
1-11.2009	25117	22419	20577	7300
12.2009	6374	6368	5526	2151

Appendix B: Additional Statistics

Table 3.24: Wage Changes for Job Stayers, by Year

Year	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1990	79799	0.0604	0.13	12.62	-0.1234	0.0869
1991	84058	0.0526	0.13	15.06	-0.1036	0.0803
1992	104759	0.0569	0.14	19.30	-0.1049	0.0956
1993	98293	0.0359	0.15	23.82	-0.1024	0.0791
1994	97999	0.0426	0.14	20.22	-0.1014	0.0790
1995	94452	0.0209	0.14	27.70	-0.0998	0.0672
1996	92769	0.0203	0.12	29.01	-0.0812	0.0618
1997	91431	0.0230	0.16	27.77	-0.0907	0.0667
1998	93479	0.0295	0.17	24.07	-0.0929	0.06.83
1999	96815	0.0242	0.14	27.61	-0.0866	0.0665
2000	98362	0.0274	0.14	24.31	-0.0906	0.0653
2001	101904	0.0195	0.15	28.74	-0.0899	0.0636
2002	99733	0.03.68	0.13	28.78	-0.0806	0.0842
2003	99809	0.0145	0.13	33.64	-0.0785	0.0617
2004	95265	0.0175	0.13	30.39	-0.0784	0.0593
2005	92321	0.0253	0.12	27.25	-0.0731	0.0622
2006	87085	0.0333	0.13	28.45	-0.0771	0.0771
2007	106553	0.0308	0.13	26.25	-0.0732	0.0679
2008	105361	0.0130	0.13	33.30	-0.0853	0.0621
2009	104307	0.0275	0.13	25.67	-0.0773	0.0637

Notes: Mean in log points, fraction in percentage points.

Table 3.25: Wage Changes for Job Stayers in the 1990s, by Period

Period	Changes Fraction	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1-11.1990	81.02	0.0592	0.11	11.05	-0.1031	0.0794
12.1990	89.78	0.0602	0.12	12.32	-0.1087	0.0840
1-11.1991	80.63	0.0518	0.11	13.65	-0.0872	0.0738
12.1991	89.16	0.0526	0.11	14.78	-0.0935	0.0779
1-11.1992	75.16	0.0571	0.12	17.95	-0.0907	0.0895
12.1992	85.74	0.0549	0.13	19.33	-0.0993	0.0918
1-11.1993	73.53	0.0367	0.12	22.43	-0.0865	0.0723
12.1993	83.43	0.0353	0.13	23.62	-0.0943	0.0754
1-11.1994	75.08	0.0435	0.12	18.52	-0.0856	0.0729
12.1994	84.29	0.0426	0.13	20.08	-0.0932	0.0767
1-11.1995	73.49	0.0203	0.12	26.79	-0.0871	0.0597
12.1995	82.65	0.0196	0.13	27.69	-0.0946	0.0634
1-11.1996	73.36	0.0191	0.10	28.40	-0.0715	0.0550
12.1996	82.33	0.0192	0.11	28.97	-0.0794	0.0594
1-11.1997	72.13	0.0225	0.15	26.75	-0.0785	0.0594
12.1997	81.56	0.0208	0.16	27.91	-0.0888	0.0632
1-11.1998	73.37	0.0292	0.15	23.04	-0.0789	0.0616
12.1998	82.85	0.0290	0.16	23.77	-0.0893	0.0660
1-11.1999	72.76	0.0242	0.12	26.58	-0.0730	0.0594
12.1999	82.97	0.0220	0.13	27.79	-0.0819	0.0621

Notes: Mean in log points, fraction in percentage points.

Table 3.26: Wage Changes for Job Stayers in the 2000s, by Period

Period	Changes Fraction	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1-11.2000	73.36	0.0263	0.12	23.35	-0.0764	0.0576
12.2000	83.94	0.0258	0.13	24.22	-0.0875	0.0620
1-11.2001	73.31	0.0190	0.13	27.58	-0.0767	0.0554
12.2001	83.47	0.0157	0.14	28.54	-0.0863	0.0564
1-11.2002	73.98	0.0363	0.11	28.12	-0.0703	0.0780
12.2002	83.28	0.0337	0.12	28.96	-0.0777	0.0792
1-11.2003	74.00	0.0135	0.11	32.64	-0.0666	0.0524
12.2003	82.54	0.0079	0.12	34.43	-0.0762	0.0520
1-11.2004	73.96	0.0162	0.11	29.48	-0.0670	0.0511
12.2004	82.88	0.0126	0.12	30.88	-0.0756	0.0520
1-11.2005	72.78	0.0235	0.10	26.35	-0.0612	0.0538
12.2005	81.31	0.0224	0.12	27.30	-0.0707	0.0574
1-11.2006	65.22	0.0310	0.11	28.01	-0.0646	0.0682
12.2006	74.18	0.0298	0.12	28.56	-0.0748	0.0716
1-11.2007	75.89	0.0279	0.11	25.08	-0.0616	0.0579
12.2007	85.58	0.0260	0.12	26.14	-0.0718	0.0606
1-11.2008	75.83	0.0116	0.11	32.85	-0.0759	0.0545
12.2008	85.48	0.0097	0.12	33.79	-0.0833	0.0571
1-11.2009	74.38	0.0276	0.10	24.11	-0.0653	0.0571
12.2009	83.97	0.0255	0.11	25.16	-0.0747	0.0592

Notes: Mean in log points, fraction in percentage points.

Table 3.27: Wage Changes for EE Transitions, by Year

Year	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1990	11133	0.0715	0.27	27.04	-0.1949	0.1702
1991	11353	0.0741	0.26	29.50	-0.1741	0.1779
1992	18463	0.1011	0.26	24.41	-0.1770	0.1910
1993	16124	0.0554	0.26	32.37	-0.1723	0.1644
1994	15596	0.0608	0.25	28.76	-0.1816	0.1587
1995	16405	0.0518	0.25	31.52	-0.1599	0.1492
1996	14178	0.0449	0.23	33.47	-0.1468	0.1413
1997	13300	0.0442	0.25	33.27	-0.1597	0.1459
1998	13948	0.0621	0.27	31.99	-0.1522	0.1629
1999	15005	0.0569	0.26	30.40	-0.1703	0.1561
2000	16983	0.0649	0.26	31.08	-0.1536	0.1634
2001	15534	0.0470	0.27	34.15	-0.1566	0.1526
2002	12868	0.0453	0.27	31.61	-0.1638	0.1419
2003	10139	0.0367	0.25	36.28	-0.1505	0.1433
2004	9340	0.0448	0.24	31.35	-0.1565	0.1367
2005	8520	0.0435	0.26	33.43	-0.1560	0.1436
2006	10007	0.0562	0.27	33.76	-0.1526	0.1626
2007	11946	0.0619	0.26	32.72	-0.1554	0.1676
2008	11322	0.0667	0.26	29.04	-0.1628	0.1606
2009	9022	0.0356	0.25	36.57	-0.1522	0.1438

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points, fraction in percentage points.

Table 3.28: Wage Changes for EE Transitions in the 1990s, by Period

Period	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1-11.1990	792.82	0.0726	0.29	31.05	-0.2024	0.1967
12.1990	2412	0.0690	0.19	16.38	-0.1679	0.1154
1-11.1991	787.64	0.0746	0.29	33.17	-0.1980	0.2037
12.1991	2689	0.0647	0.19	19.23	-0.1562	0.1173
1-11.1992	1255.45	0.1035	0.29	28.69	-0.1967	0.2192
12.1992	4653	0.0866	0.18	16.33	-0.1404	0.1309
1-11.1993	1045.27	0.0610	0.29	36.41	-0.1991	0.2035
12.1993	4626	0.0417	0.16	23.19	-0.1262	0.0924
1-11.1994	100.1936	0.0637	0.28	32.61	-0.1997	0.1914
12.1994	4394	0.0510	0.16	20.87	-0.1229	0.0968
1-11.1995	989.18	0.0617	0.29	37.08	-0.1785	0.2030
12.1995	5524	0.0285	0.15	22.18	-0.1107	0.0681
1-11.1996	899.09	0.0511	0.26	37.60	-0.1651	0.1930
12.1996	4288	0.0272	0.14	25.77	-0.1013	0.0718
1-11.1997	859	0.0493	0.28	36.62	-0.1776	0.1915
12.1997	3851	0.0280	0.17	27.16	-0.1086	0.0789
1-11.1998	907.73	0.0661	0.30	36.55	-0.1678	0.1997
12.1998	3963	0.0502	0.20	21.55	-0.1171	0.0962
1-11.1999	1026.27	0.0648	0.29	32.46	-0.1964	0.1953
12.1999	3716	0.0374	0.20	26.10	-0.1178	0.0923

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points, fraction in percentage points.

Table 3.29: Wage Changes for EE Transitions in the 2000s, by Period

Period	Changes N	Changes Mean	Changes St. Dev.	Decreases Fraction	Decreases Mean	Increases Mean
1-11.2000	1160.27	0.0732	0.28	32.76	-0.1737	0.1915
12.2000	4220	0.0413	0.19	25.69	-0.1200	0.0970
1-11.2001	1049.45	0.0525	0.29	37.53	-0.1722	0.1975
12.2001	3990	0.0260	0.17	25.84	-0.1176	0.0760
1-11.2002	837	0.0433	0.30	34.97	-0.1970	0.1670
12.2002	3661	0.0480	0.16	25.92	-0.0954	0.0982
1-11.2003	658.73	0.0456	0.28	37.85	-0.1757	0.1905
12.2003	2893	0.090	0.14	33.74	-0.0981	0.0636
1-11.2004	606.73	0.0513	0.27	34.03	-0.1772	0.1686
12.2004	2666	0.0205	0.15	27.76	-0.1049	0.0688
1-11.2005	566.64	0.0470	0.28	36.10	-0.1757	0.1739
12.2005	2287	0.0338	0.19	28.60	-0.1002	0.0875
1-11.2006	675	0.0617	0.30	36.69	-0.1739	0.1974
12.2006	2582	0.0389	0.18	25.56	-0.1163	0.0922
1-11.2007	855.91	0.0655	0.28	35.05	-0.1719	0.1934
12.2007	2531	0.0482	0.19	23.94	-0.1191	0.1009
1-11.2008	813	0.0715	0.27	31.25	-0.1752	0.1930
12.2008	2379	0.0411	0.17	25.18	-0.1134	0.0930
1-11.2009	629.55	0.0354	0.27	40.43	-0.1667	0.1679
12.2009	2097	0.0352	0.18	25.04	-0.1115	0.0842

Notes: Restricted to uncensored observations, and full-time, non-trainee, sole employment after the transition. Mean in log points, fraction in percentage points.