Separations, Sorting and Cyclical Unemployment*

JOB MARKET PAPER

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Abstract

This paper establishes a new fact about the compositional changes in the pool of unemployed over the U.S. business cycle and evaluates a number of theories that can potentially explain it. Using longitudinal micro-data from the Current Population Survey 1979-2008, it documents that in recessions the pool of unemployed shifts towards workers with high wages in their previous job. Moreover, it shows that these changes in the composition of the unemployed are mainly due to the higher cyclicality of separations for high-wage workers, and not driven by differences in the cyclicality of job-finding rates. A search-matching model with endogenous separations and worker heterogeneity in terms of ability has difficulty in explaining these patterns. But an extension of the model with credit-constraint shocks does much better in accounting for the new facts. The reason is that, at the productivity threshold where separations occur, matches with high-ability workers produce more negative cash flows and separations of these workers are thus more sensitive to a tightening of credit than separations of low-ability workers.

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1 Introduction

This paper establishes a new fact about the compositional changes in the pool of unemployed over the U.S. business cycle and evaluates a number of theories that can potentially explain it. Using longitudinal micro-data from the Current Population Survey (CPS) 1979-2008, I document that in recessions the pool of unemployed shifts towards workers with high wages in their previous job. This cyclical pattern is robust to many different empirical specifications. Controlling for observable characteristics such as education, age, occupation etc. in the wage, I show that the share of unemployed with high residual wages still increases in recessions, although the magnitude of the increase is smaller than for the raw wage measure. This finding suggests that both observed and unobserved factors explain the shift towards high-wage workers in recessions. I also investigate whether the compositional shift is due to differences in the cyclicality of separation or job-finding rates across wage groups, and find that the compositional shift is almost entirely driven by separations.

These empirical patterns may appear to contradict findings from a related literature on the cyclicality of real wages. Specifically, Solon, Barsky and Parker (1994) documented that the measured cyclicality of aggregate real wages is downward biased, because the typical *employed* person is of higher ability in recessions. Hines, Hoynes and Krueger (2001), however, showed that Solon, Barsky and Parker's result relies on the weighting of aggregate real wages by hours worked. With un-weighted wage data, composition bias has almost no effect on the cyclicality of real wages, suggesting that is not the composition of the employed that changes over the business cycles but rather the hours worked by different skill groups. Moreover, changes in the composition of the employed do not necessarily translate into changes in the pool of unemployed in the opposite direction if the average quality between the pools differs. In fact, I show that large shifts towards high-wage workers in the pool of unemployed are fully consistent with small shifts towards high-wage workers in the pool of employed.

My empirical findings have potentially important implications for models of aggregate fluctuations in the labor market, as changes in the pool of unemployed feed back into firms' incentives for hiring. Contrary to Pries (2008), who assumes that the pool of unemployed shifts towards low-ability workers, shifts towards high-ability workers in recessions lead to a dampening of productivity shocks. The reason is that when unemployment shifts towards the more able, the probability that a firm finds a worker of high ability goes up, which raises returns to posting vacancies. This poses an additional challenge to the recent literature on the "unemployment volatility puzzle" (see Shimer, 2005), as shifts towards high-ability workers in recessions may dampen the response of hiring and unemployment to aggregate productivity shocks.

Given the importance of the new fact I document in the first part of the paper, the second part of the paper tries to explain it. To do so, I first set up a search-matching model with match-specific productivity shocks, endogenous separations and worker heterogeneity in terms of ability.[1] The baseline model, however, implies shifts in the pool of unemployed towards low-ability workers in recessions, which is inconsistent with the new facts. I also explore other calibrations of the model, as well as models with different types of worker heterogeneities such as differences in bargaining power or home production. All these models, however, have difficulties in replicating the key facts summarized above. Therefore, I offer two extensions of the model that can potentially explain the more cyclical nature of separations for high-ability workers.

One explanation is that many layoffs in downturns occur due to firm and plant death. These shocks affect workers indiscriminately of type and thus increase separations more in percentage terms for those with lower average separation rates (i.e., high-ability workers). The model, however, cannot fully explain the higher cyclicality of separations for high-ability workers because, with such death shocks, differences in the cyclicality of separation rates between low-wage and high-wage individuals are limited by differences in the average separation rates between the two groups.

I thus propose another extension of the model with credit shocks, where firms are constrained to produce positive cash flows in recessions. This also produces more cyclical separations for high-ability workers. The idea is that it is more difficult to obtain outside financing in recessions as liquidity dries up in financial markets. In the baseline model with efficient separations, worker-firm matches produce negative cash flows at the productivity threshold where separations occur. The firm is willing to pay the worker above current match productivity, because it

[1] Bils, Chang and Kim (2009) also study the cyclicality of separations for different wage and hours groups. However, they pay little attention to compositional changes in the pool of unemployed in terms of ability. See also below in Section 2 below for a discussion of their empirical results from the Survey of Income and Program Participation (SIPP).

is compensated by expected positive future cash flows. Thus, if firms face constraints on their cash flows in recessions, workers and firms may separate even though it would be in the interest of both parties to continue the relationship. This mechanism is stronger for high-ability workers, because they produce larger negative cash flows at the efficient (unconstrained) separation threshold. Therefore, separations of these workers are more sensitive to a tightening of credit. As a result, the model produces more cyclical separations for high-ability workers, consistent with the empirical patterns in the U.S. data.

The remainder of the paper is organized as follows. Section 2 describes the CPS data and carries out the empirical analysis. Section 3 sets up the search-matching model, discusses alternative calibration strategies, and studies the model with firm and plant death. Section 4 extends the model with credit-constraint shocks. Section 5 concludes.

2 Data

I use U.S. micro-data from the Current Population Survey (CPS) for the period 1979-2008 to estimate monthly transition probabilities from employment to unemployment and vice versa. The CPS is the main labor force survey for the U.S., representative of the population aged 15 and older. It has a rotating panel structure, where households are surveyed for four consecutive months, rotated out of the panel for eight months, and then surveyed again for another four consecutive months, as illustrated in Figure 1. Note that the CPS records the labor-force status for each person in the sample each month. Weekly hours and earnings, however, are collected only in the fourth and eighth interview of the survey, referred to as the Outgoing Rotation Groups (ORG).

Figure 1: *CPS panel structure by month and interview number*

2.1 Sample Criteria and Measurement

I am interested in the wage of those who lose their job and become unemployed. Wage data is available only for the fourth and the eighth interview of each household. I restrict my sample to all persons with available wage data from the fourth interview and analyse the employment outcomes in subsequent months. I do not use wage data from the eighth interview as this is the final interview in the CPS panel and I want to avoid possible selection effects associated with including wages after job loss.[2]

I restrict my sample to individuals of age 19 to 64 who worked in the private sector, are not self-employed and not self-incorporated. I also trim the sample for outliers exluding individuals with a wage above the 99.75th or below the 0.25th percentile each year and individuals with weekly hours below 5 or above 80. The sample size is 1,369,741 individuals, where each individual has up to 3 monthly transitions between labor market states (between interviews 5 to 6, 6 to 7 and 7 to 8).

The CPS does not follow individuals who move out from an address surveyed in a previous month.[3] This gives rise to substantial attrition between the fourth interview when individuals report their wage and the interviews 9, 10, 11 and 12 months later (as Figure 1 shows, there is a gap of 8 months between the 4th and the 5th interview): 27% of the individuals in my sample had no match in interviews 5-8. Similarily to Bleakly, Ferris and Fuhrer (1999), I adjust the survey weights to account for attrition. More precisely, I run a logit regression of the likelihood of remaining in the sample for the interviews 5 to 8 on observable characteristics (such as sex, age, education, race and marital status) for each year, and multiply the existing survey weight with the inverse of the predicted value of the logit regression. This deflates the weight for groups and years with low attrition rates.[4]

[2] The main worry is that individuals who separate in recessions tend to have lower wages on their *new* job, because it has been documented that wages for new hires are more responsive to the business cycle. See, e.g., Bils (1985) or, more recently, Haefke, Sonntag and van Rens (2009).

[3] See Madrian and Lefgren (1999) for details about merging CPS files. Because of moving in and out at given household adresses, one has to eliminate invalid matches based on demographic information. I use the s|r|a criterion of Madrian and Lefgren, because it appears to yield a relatively good trade-off between accepting invalid matches and rejecting valid matches. The criterion keeps as valid matches only those with the same sex, race and an age difference of 0-2 years.

[4] Abowd and Zellner (1985) propose a procedure of reweighing the data that minimizes the difference between the stocks implied by the matched worker flow data and the official CPS stocks. Unfortunately, this procedure is not available here because the CPS does not report the stocks of unemployed workers by wage on the previous job.

The selected sample excludes unemployed individuals who have been unemployed for more than 12 months. This may lead to biases in the estimates of the average and the cyclicality of job findings rates (in particular, if job-finding rates are duration dependent). Notice, however, that the median duration of unemployment was less than three months for the entire sample period according to official statistics of the Bureau of Labor Statistics (BLS), and the fraction of those with unemploymend durations above one year averaged only 8.8% over the sample period with a maximum of 13.3% in 1983.[5] This suggests that the constraint imposed by the sample-selection criterion is relatively minor.

Finally, the sample does not include those who were classified as out of the labor force at the time of their 4th CPS interview. For this reason, movements from out of the labor force into unemployement and employment are not included in my sample. As argued by Shimer (2007) and others, movements between out of the labor force and unemployment are relatively acyclical and contribute little to the overall variation in unemployment. Of course, it is still possible that movements in and out of the labor force are different across groups and that these differences cancel out in the aggregate. In any event, movements between out of the labor force and unemployment are another potential margin of cyclical changes in the composition of the pool of unemployed, which is omitted from my analysis.

2.2 The Cyclicality of the Wage of Job Losers

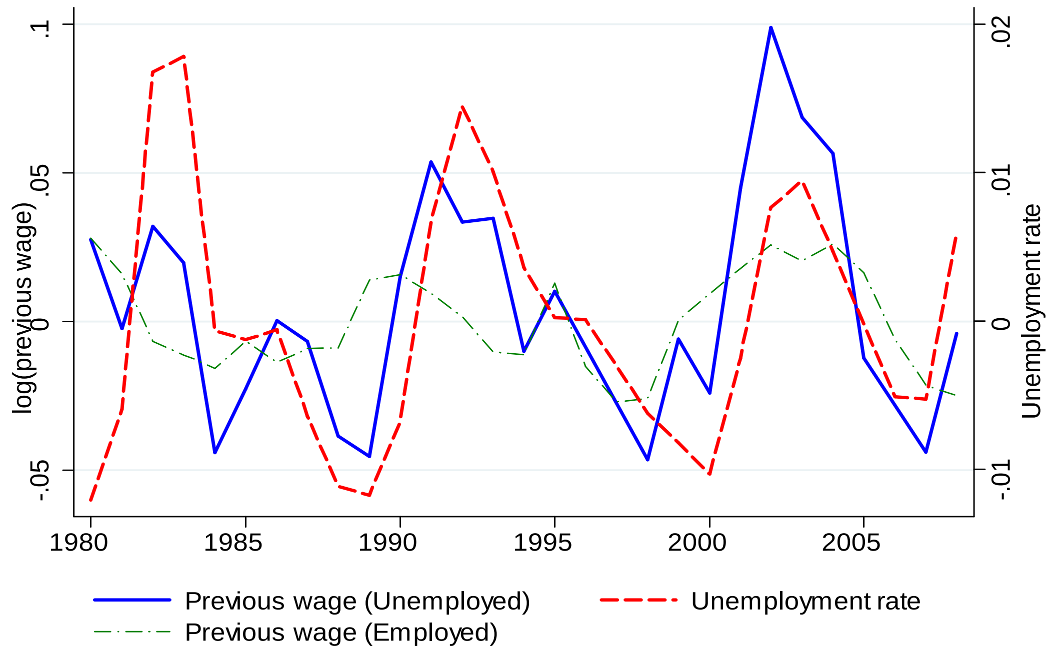
Does the composition of the unemployed change over the business cycle? In particular, are there changes in the pool by ability? To answer these questions, I use the wage on the previous job as an indicator of ability. Figure 2 plots the average wage of those who lost their job over the previous year, as well as the average wage of those who remained employed. More precisely, I plot the yearly average wage for those who were employed in interview 4 but unempoyed in interview 8 of the CPS, as well as the average wage of those who remained employed. As is apparent from the plot, the average wage of the unemployed is strongly and positively correlated with the aggregate unemployment rate (the correlation coefficient is 0.55).[6]

Figure 3 shows that, when I remove year effects, the average wage for the unemployed is

[5] These numbers are taken from the OECD's statistics of "Incidence of unemployment by duration".

[6] The unemployment rate is taken from the official tables of the Bureau of Labor Statistics.

Figure 2: *Average wage from previous year by employment status*



Notes: Linear regression for the unemployed (t-stat in parentheses): log(w) = 0(-0.0) + 2.79(3.39)*U.
Correlation coefficient = 0.55. All series are yearly averages and hp-filtered with smoothing parameter 100.

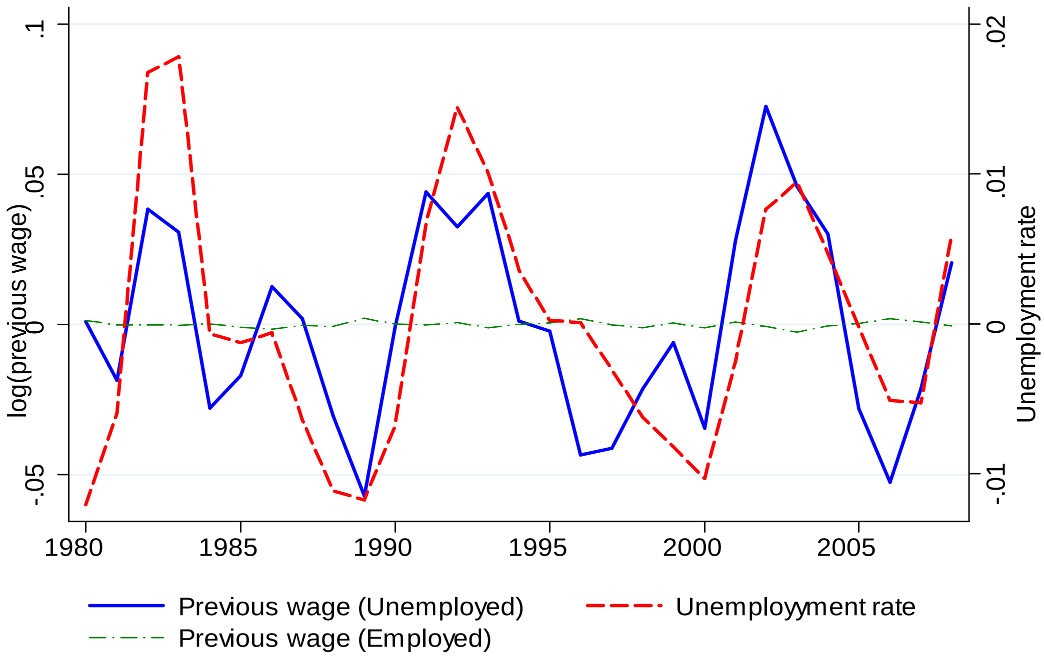
even more closely correlated with the unemployment rate, with a correlation coefficient of 0.72, suggesting that the results are not driven by the cyclical behavior of real wages.[7]

Figure 4 shows the same plot but for the residual of a Mincer-style regression of the wage on observable characteristics such as age, gender, marital status, education and race, and dummies for state, industry, occupation and year. The average wage residual is still strongly counter-cyclical for those who lost their job over the previous year, with a correlation with the unemployment rate of 0.62. The magnitude is smaller as a percentage-point increase in the unemployment rate leads to a 1.1% increase in the average residual wage of the unemployed, compared to a 2.8% increase in the average (not residual) wage in Figure 2. This suggests that both observed and unobserved factors contribute to the compositional changes in the unemployment pool over the business cycle.

One thing to keep in mind is that the reported series are HP-filtered such that the mean is zero for both the employed and unemployed over the entire sample period. The mean of the

[7] By definition, the average wage residual is zero for each year for the full sample and close to zero for the employed as they represent over 90 % of the full sample.

Figure 3: *Average wage from previous year by employment status (residuals from a regression of the log wage on year dummies)*

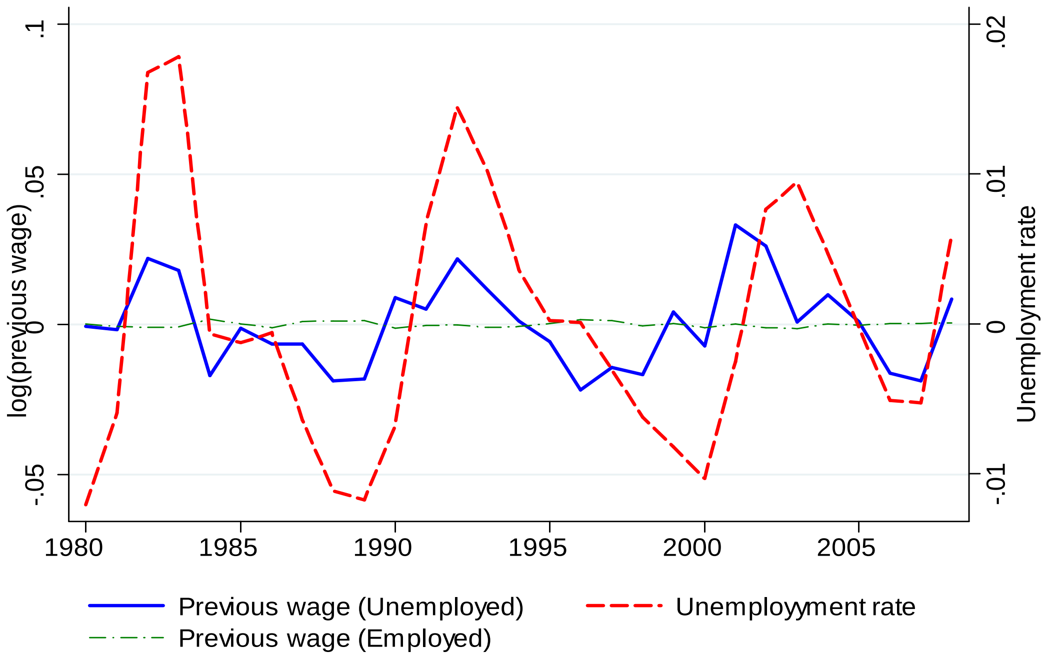


Notes: Linear regression for the unemployed (t-stat in parentheses): log(w) = 0(0.0) + 2.9(5.87)*U.
Correlation coefficient = 0.72. All series are yearly averages and hp-filtered with smoothing parameter 100.

unfiltered series is, however, considerably lower for those who lose their job, as opposed to those who remain employed. This suggests that the unemployed are on average of lower quality, but become more similar to the employed in a recession.

One might be concerned about wage compression and argue that the wage differential between those who lose their job and those who remain employed narrows in a recession, simply because overall wage dispersion becomes smaller at the same time. To evaluate this possibility, I attribute an ordinal wage rank to each individual in my data set (the rank in the wage distribution in a given year is defined by lining up all individuals according to their current wage from the lowest to the highest on the unit interval). If wage compression drives the patterns in Figures 2-4, then the average wage rank should show no correlation with the aggregate unemployment rate. Figure 5, however, shows a very strong correlation of the average wage rank of the unemployed with the aggregate unemployment rate. The correlation coefficient is 0.72, suggesting that wage compression plays no role. In terms of the magnitude, a percentage-point

Figure 4: *Average wage from previous year by employment status (residuals from a regression of the log wage on year dummies and observable characteristics)*



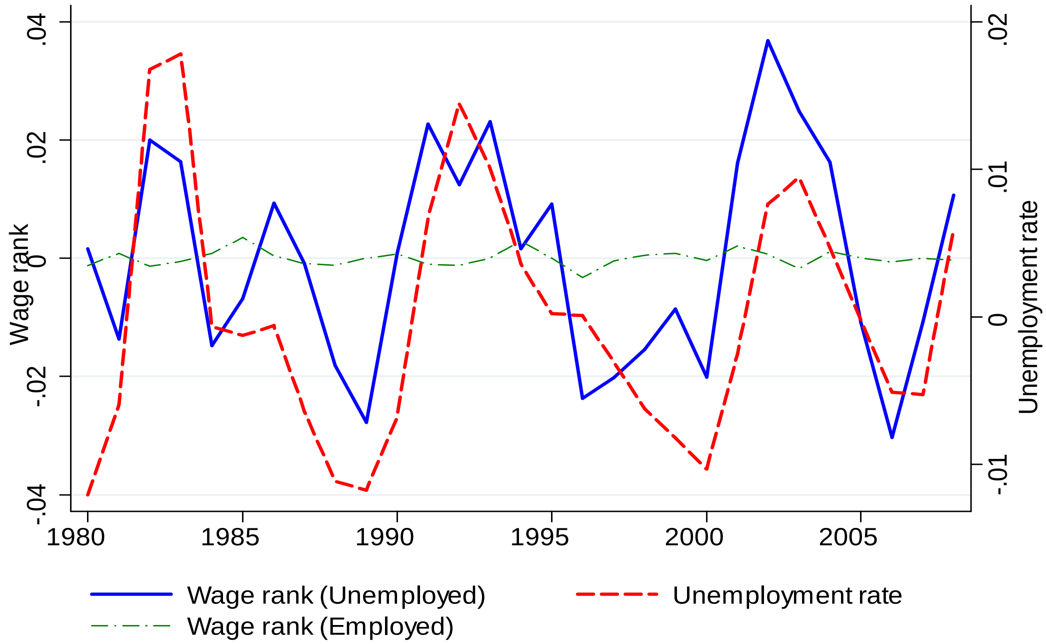
Notes: Linear regression for the unemployed (t-stat in parentheses): log(w) = 0(0.0) + 1.1(7.33)*U.
Correlation coefficient = 0.62. All series are yearly averages and hp-filtered with smoothing parameter 100.

increase in the unemployment rate is associated with a 1.5 percentage-point increase in the average wage rank of the job losers, which represents a substantial shift in the composition of the pool of unemployed.

2.3 The Cyclicality of Separations and Job Findings by Wage Group

Changes in the composition of the pool of unemployed over the business cycle can arise because of different behavior of inflows into and/or the outflows from unemployment. For this reason, I analyse in more detail the worker *flow* data from my CPS sample to determine whether the patterns documented in the previous section are due to job separations or the job findings. In particular, I divide the sample in each year in those below and above the median wage and analyse the cyclical behavior of the separation and job-finding rate for each of these groups. Job separations and findings are defined as the percentage of those who changed their employment status (from E (employment) to U (unemployment) or from U to E). The groups are divided into

Figure 5: *Average wage rank by employment status*



Notes: Linear regression for the unemployed (t-stat in parentheses): Wage rank = 0(0.0) + 1.54(5.92)*U. Correlation coefficient = 0.72. All series are yearly averages and hp-filtered with smoothing parameter 100.

below or above the median wage in interview 4, and the transitions are analysed for subsequent interviews (i.e., monthly transitions between interviews 5 to 6, 6 to 7 and 7 to 8).

Measurement

Elsby, Michaels and Solon (2009) show that one can decompose the contributions of separations (s) and job findings (f) to changes in the unemployment rate approximately into

$$dU_t \approx U_t(1-U_t)\left[d\ln s_t - d\ln f_t\right]. \tag{1}$$

Now, the share of group i in the pool of unemployed is defined as

$$\phi_{it}^U = \psi_i^U \frac{U_{it}}{U_t}, \tag{2}$$

where U_{it} is the unemployment rate of group i at time t and ψ_i^U the population share for group i (assumed to be constant). Given equations (1) and (2), one can show that changes in the share of group i in the pool of unemployed can be decomposed into

$$d\phi_{it}^{U} \approx \phi_{it}^{U} \begin{pmatrix} (1-U_{it})\left[d\ln s_{it} - d\ln f_{it}\right] \\ -(1-U_{t})\left[d\ln s_{t} - d\ln f_{t}\right] \end{pmatrix}, \tag{3}$$

which implies that changes in the share of group i are related to changes in the *log* of the separation and job-finding rate of group i relative to the average. More importantly, since $(1 - U_{it})$ is very similar across groups, one can directly conclude from the magnitude of the changes in the log separation and job-finding rates to which margins are more important for the changes in the composition of the pool. To understand how separations and job findings relate to cyclical changes in the unemployment rate, one thus has to relate the changes in the log of the separation and job-finding rate to the aggregate unemployment rate (or other cyclical indicators). For this reason, I run the following regressions:

$$\ln x_{it} = \alpha_i^x + \beta_i^x \ln U_t + \varepsilon_{it}^x, \tag{4}$$

where x_{it} stands for s_{it} (separation rate), f_{it} (job-finding rate) or U_{it} (unemployment rate) for group i at time t and the measure of cyclicality is the percentage increase in x_{it} in response to a 1% increase in the aggregate unemployment rate (the coefficient β_i^x). All series are monthly, seasonally adjusted, and detrended with an HP-filter with smoothing parameter 900,000.

Results

Table 1 summarizes the main results for different groups in terms of the average as well as the cyclicality of separation and job-finding rates. The first two columns split the sample into those below and above the median wage. Columns 3 and 4 report the results for those below and above the median residual wage.

Not surprisingly, separations are lower for high-wage workers than for low-wage workers on average. The main result is that the cyclicality of separations is almost twice as large for individuals with high wages compared to those below the median. The difference is a bit smaller when looking at the cyclicality of separations for those below and above the median residual

Table 1. CPS 1979-2008: The cyclicality of separation and job-finding rates, by wage group

		Log(hourly wage)		Mincer residual	
		low	high	low	high
Separations	Average	0.012	0.007	0.010	0.008
	Cyclicality	**0.40**	**0.75**	**0.45**	**0.67**
	(s.e.)	(0.082)***	(0.099)***	(0.063)***	(0.085)***
Job findings	Average	0.318	0.301	0.309	0.313
	Cyclicality	**-0.57**	**-0.72**	**-0.68**	**-0.61**
	(s.e.)	(0.059)***	(0.069)***	(0.073)***	(0.077)***
Unemployment	Average	0.036	0.023	0.033	0.025
	Cyclicality	**0.81**	**1.25**	**0.91**	**1.11**
	(s.e.)	(0.024)***	(0.030)***	(0.027)***	(0.035)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000. The cylicality is measured as the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, job-finding or unemployment rate of group i at time t and Ut is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

wage: The ratio of $\frac{\beta^{sep}_{low}}{\beta^{sep}_{high}}$ is 0.68 compared to 0.54 for the cyclicality with the raw wage measure.

Job-finding rates are of similar size, on average, for both groups, and also their cyclicality is very similar across groups: The cyclicality of job findings is slightly more cyclical for those above the median wage, but the pattern reverses for the residuals and the differences are not statistically significant. Overall, I conclude that changes in the composition of the pool in terms of the previous wage are driven:

1. almost entirely by the different cyclicality of separations as opposed to job findings and

2. by observable as well as unobservable characteristics of the unemployed.

These facts are robust across a large range of different specifications and sample selection criteria. Appendix Tables A.1, A.2 and A.3 show very similar results for different sample restrictions (age 25-54, men only, full-time workers only, college educated only, years 1990-2008) and different filters. The patterns are also similar when one includes those OLF (out of the labor force) or excludes those on temporary layoff. Finally, I use Fujita and Ramey's (2009) adjustment for time aggregation bias and find that the differences in the cyclicality of separations are even stronger for those below and above the median wage.

Job-to-Job Transitions

The measure of job separation above does not include job-to-job transitions (in other words, job separations that do not result in an intervening spell of unemployment). The original CPS did not ask respondents about job switches, but fortunately with the redesign of the CPS in 1994, it became possible to identify those who switched their job between two monthly interviews (see Fallick and Fleischman, 2004, for details). Table 2 shows the average and the cyclicality of job-to-job transitions for the same groups as in Table 1. As in Fallick and Fleischman, the monthly job-to-job transitions are about twice as large as the flow from E to U. The job-to-job transitions are procyclical, but less so for individuals with high wages. In particular, the cyclicality for those with high residual wages is -0.10, compared to -0.25 for those with low residual wages. Even though these differences are only marginally statistically significant (at the 10% level), this evidence does not support the view that the high cyclicality of separations for high-wage workers is driven by the fact that direct job-to-job transitions decrease strongly during recessions for this group. On the contrary, it appears that job-to-job transitions decrease more for low-wage workers in recessions and thus one would expect that separations into unemployment to be more cyclical for the *low*-wage group.

In summary, the data strongly suggests the unemployment pool shifts towards high-ability individuals in recessions, and this shift is mainly due to job separations.

Table 2. CPS 1994-2008: The cyclicality of job-to-job transition rate, by wage group

		Log(hourly wage)		Mincer residual	
		low	high	low	high
Job-to-job transitions	Average	0.023	0.018	0.021	0.019
	Cyclicality	**-0.22**	**-0.13**	**-0.25**	**-0.10**
	(s.e.)	(0.058)***	(0.074)*	(0.064)***	(0.075)

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. See notes in Table 1 for further details.

2.4 Relation to Previous Research

Bils, Chang and Kim (2009) find similar patterns in the data for low-wage vs. high-wage workers from the Survey of Income and Program Participation (SIPP), but they focus their attention on the cyclical nature of *employment* for these groups and pay little attention to the question of cyclical changes in the composition of the pool of unemployed. More precisely, they split their sample into four groups: by low or high hours and by low or high wages. Averaging the cyclicality of separations for the wage groups, one finds that the cyclicality of separations is about 20% lower for the low-wage group, compared to 35-50% in the CPS data. One possible explanation for the quantitatively smaller effect is that Bils, Chang and Kim average wages before and after job loss, which introduces a potential selection effect: workers who separate into unemployment in a recession are likely to receive lower wages on their new job and thus, are more likely to be classified in the low-wage group.[8,9]

Solon, Barsky and Parker (1994) show that there is a substantial composition bias when looking at the cyclicality of aggregate real wages. The employed become *more* skilled during recessions, leading the researcher to underestimate the cyclicality of real wages when looking at aggregate wage data. This evidence seems to be in contrast with the facts presented above, because it suggests that the proportion of high-wage workers *among the employed* increases in recessions. However, their evidence relies on composition bias in the aggregate hourly wage, which is a weighted average by hours. Therefore, composition bias could be driven either by a higher cyclicality of hours for the low skilled (the intensive margin) or a higher cyclicality of employment for the low skilled (the extensive margin). In fact, Hines, Hoynes and Krueger (2001) show that Solon, Barsky and Parker's result relies on the weighting of aggregate real wages by hours worked. They demonstrate that with un-weighted wage data composition bias has almost no effect on the cyclicality of real wages, suggesting that it is not the composition of the employed that changes over the business cycle but rather the hours worked by different skill groups.

[8] There is a large body of evidence that shows that wages of new hires strongly respond to the business cycle (see, e.g., Bils, 1985, or Haefke et al., 2009).

[9] Other differences between their and my analysis is that they use aggregate total hours as a cyclical indicator instead of the aggregate unemployment rate and they cover a smaller number of years (from 1983 to 2005, with some gaps).

Another important observation is that the pool of unemployed and the pool of employed do not necessarily have to shift in the same direction if the pools differ in the average quality. Specifically, since the typical unemployed is of lower ability than the typical employed, a transition of a worker from the lower part of the distribution of the pool of employed to the upper part of the distribution of the pool of unemployed can make both pools better off. More formally, one can approximate the relationship between changes in the share of group i in the pool of unemployed ($d\phi_{it}^U$) and changes in the share of group i in the pool of employed ($d\phi_{it}^E$) as follows:

$$d\phi_{it}^E \approx \phi_{it}^E[-2U_t d\phi_{it}^U + dU_t(1 - 2\phi_{it}^U)], \tag{5}$$

which implies that if the shares of the two groups are the same ($\phi_{it}^U = 0.5$), then the pools must sort in opposite directions. However, in reality the share of the low-wage workers among the unemployed is higher ($\phi_{low,t}^U = 0.61$ in my CPS sample) and thus shifts do not necessarily go in the opposite direction. Moreover, changes in the group share among the unemployed lead to much smaller changes in the group share among the employed, because the group of unemployed is so much smaller compared to the group of employed. In fact, one can compute the response of the share of the low-wage types from the estimates in Table 1, and then use the formula in equation (5) to compute the implied change in the share in the pool of employed. The results are as follows:

$$\begin{aligned} \frac{d\phi_{low,t}^U}{dU_t} &\approx -1.98 \\ \frac{d\phi_{low,t}^E}{dU_t} &\approx -0.05, \end{aligned}$$

which says that the share of the low-wage types decreases by almost two percentage points in response to a one percentage-point increase in the aggregate unemployment rate. These results also imply that the pool of employed shifts in the *same* direction, but the shift is of a much smaller magnitude than for the pool of unemployed. A percentage-point increase in the unemployment rate decreases the share of the low-wage types by 0.05 percentage points. To conclude, large shifts in recessions towards high-wage workers in the pool of unemployed are fully consistent with small shifts towards high-wage workers in the pool of employed.

3 Model

In this and the following section I evaluate a number of theories that can potentially explain the compositional shifts in the pool of unemployed over the U.S. business cycle. I start with an extension of the standard search-matching model[10] to worker heterogeneity, and find that it has difficulty to replicate the facts summarized above. I then consider further extensions of this baseline model that can potentially account for the documented facts.

In the baseline model, there are two types of workers (indexed by i) who differ in their market productivity a_i and potentially other parameters. Similar to Bils, Chang and Kim (2009), I assume that worker ability is observable to the potential employer and thus firms can direct their search to a particular worker type.[11]More precisely, there is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function:

$$M_i = \kappa u_i^{\eta} v_i^{1-\eta}. \tag{6}$$

The job finding probability is $p(\theta_i) = \frac{M_i}{u_i}$ and the hiring rate $q(\theta_i) = \frac{M_i}{v_i}$.

Match productivity is defined as zxa_i where z is aggregate productivity, x match-specific productivity and a_i worker-specific productivity. Match-specific productivity is assumed to follow an AR(1) process as discussed below in the calibration strategy. I assume that all matches start at the median match productivity $\bar{x}$.

Let's proceed to describe the value functions of the workers and firms. The value function of an unemployed worker of type i is:

$$U_i\left(z\right) = b_i + \beta E\left[(1 - f(\theta_i))U_i(z') + f(\theta_i)W_i(z', \bar{x}) \middle| \, z \right], \tag{7}$$

where aggregate productivity z is the aggregate state. The value of being unemployed depends on the unemployment benefit b_i, which potentially depends on worker type, and the discounted

[10] The main reference is Pissarides (2000). I deviate from his model by allowing match-specific productivity shocks to be correlated across time.

[11] Appendix A.1 discusses a model where worker ability is unobservable by the employer and thus search on the firm is non-directed. The results of the model with non-directed search are similar to the model with directed search; in particular, the assumption of non-directed search has little impact on the cyclicality of separations for different ability groups.

value of staying unemployed next period or having a job with value $W_i(z', \bar{x})$.

The value function of an employed worker is:

$$W_i(z,x) = w_i(z,x) + \beta E\left[\max\left\{W_i(z',x'), U_i(z')\right\}\big|\, z, x\right], \tag{8}$$

which depends on the utility from the current wage and the discounted future expected value. Whenever the value of the job W_i is lower then the value of being unemployed U_i, the worker will separate and thus receive the value $U_i(z')$ next period.

The value of posting a vacancy for a firm is:

$$V_i(z) = -c_i + \beta E\left[(1-q(\theta_i))V_i(z') + q(\theta_i)J_i(z,\bar{x})\big|\, z\right], \tag{9}$$

which depends on the vacancy posting cost c_i and the discounted future expected value. Note that $q(\theta_i)$ is the firms hiring rate, the rate at which it fills a vacancy posted.

The value of a filled vacancy is:

$$J_i(z,x) = zxa_i - w_i(z,x) + \beta E\left[\max\left\{J_i(z',x'), V_i(z')\right\}\Bigg|\, z, x\right], \tag{10}$$

which depends on the cash flow (productivity minus the wage) and the discounted future expected value. Note that the firm will fire the worker whenever the value of the filled vacancy is lower than the value of posting a vacancy.

Wages are determined by standard Nash-bargaining and split the joint surplus from the employment relationship according to the Nash-bargaining solution:

$$[W_i(z,x) - U_i(z)] = \frac{\alpha}{1-\alpha}[J_i(z,x) - V_i(z)], \tag{11}$$

where α is the bargaining share of the worker.

Firm-worker matches are dissolved whenever the joint surplus from the relationship ($S_i(z,x) = W_i(z,x) - U_i(z) + J_i(z,x) - V_i(z)$) is smaller than zero, which implies that the reservation match productivity $R_i(z)$, i.e., the level of match-specific productivity x below which the employment relationship is dissolved, satisfies:

$$S_i(z, R_i(z)) = 0. \tag{12}$$

I refer to (12) as the efficient-separation condition. Separations are always in the interest of both parties and never unilateral (thus efficient).

A directed search equilibrium is defined as the reservation match productivity $R_i(z)$, the wage schedules $w_i(z, x)$, the labor market tightness $\theta_i(z)$ and the value functions $U_i(z)$,$W_i(z, x)$,$V_i(z)$ and $J_i(z, x)$ that satisfy the: 1. Nash-bargaining solution (11), 2. efficient-separation condition (12), 3. zero-profit condition: $V_i(z) = 0$ and 4. value functions (7), (8), (9) and (10).

3.1 Calibration

The main parameters of the model are calibrated to standard values in the literature. The following tabulation summarizes the calibration strategy.

Tabulation of the calibrated values of the main parameters of the model:

Parameter	Parameter name	Source/Target
$\beta = 0.9966$	Discount factor	r = 4.17%
$c_{high} = 0.64$; $c_{low} = 0.20$ (1)	Vacancy-posting cost	Monthly job-finding rate = 0.3
$\eta = 0.5$	Elasticity of matching function	Micro studies
$\kappa = 0.3$	Matching efficiency	$\theta = 1$
$\alpha = 0.5$	Worker's bargaining power	Hosios condition
b = 0.6	Unemployment benefit	Shimer (2005); Hagedorn and Manovskii (2008)
$\ln(x_{t+1}) = 0.98\ln(x_t) + \varepsilon_t$	Match-specific productivity	Bils, Chang and Kim (2009)
$\sigma_\varepsilon = 0.03$	Std of match-specific shocks	Monthly separation rate = 0.01
$z_g = 1.02$; $z_b = 0.98$	Aggregate state	Shimer (2005)
$\pi_{gb} = \pi_{bg} = 1 / 24$	Transition probabilities	Duration of recession = 2 years
$a_{high} / a_{low} = 1.2 / 0.8$	Ratio of worker productivity	Wage dispersion in CPS data

(1) The vacancy posting costs are chosen to match a monthly job-finding rate of 0.3. Therefore, the values change for alternative calibrations of the model.

The parameters are chosen to be the same for both groups of workers unless otherwise noted. The vacancy posting cost c_i is calibrated internally to match a monthly job-finding rate of 0.3 for both groups (as in the CPS data). The elasticity of the matching function η accords with estimates from micro studies and is set to 0.5. The matching efficiency κ is a free parameter in the model and chosen such that $\theta = 1$. The worker's bargaining power is set equal to the elasticity of the matching function in order to satisfy the Hosios condition. The log of match productivity is assumed to follow an AR(1) process with autocorrelation coefficient 0.98. The standard deviation of match productivity shocks is set to match an average monthly separation rate of 0.01, as in the CPS data. I discretize the state space in terms of match productivities x with Tauchen's (1986) algorithm. Aggregate productivity z is assumed to take on two values, set to match a standard deviation of aggregate labor productivity of 0.02, as reported by Shimer (2005). The productivitiy parameters a_{low} and a_{high} are assumed to be 0.8 and 1.2. In the CPS data the ratio of the wage of the group below and above the median wage is around 0.4. Thus the assumption of $a_{high}/a_{low} = 1.2/0.8$ is a conservative estimate of differences in worker productivites. The unemployment benefit is assumed to be constant and equal to 0.6 (somewhere in between the extreme assumptions of Shimer (2005) and Hagedorn and Manovskii (2008)). The assumption of a constant benefit by worker type implies that, at the median match productivity $\bar{x} = 1$, the ratio of benefits over worker productivity is 0.75 for the low types and 0.5 for the high types. This strategy is motived by two main observations: First, wages are generally replaced only up to specified limit. In the U.S., the maximum unemployment benefit is binding for approximately 35% of unemployed workers (see Krueger and Meyer, 2002). Second, the parameter b should also capture the utility derived from additional leisure during unemployment as well as consumption provided by additional home production, which is likely to be less than perfectly correlated with market ability a. For these reasons, replacement rates should be higher for the low-ability group.

3.2 Results

Table 3 reports results for the baseline calibration. The same filtering methods as for the empirical results from the CPS are applied to the simulated time series . Evidently, the model

Table 3. Baseline model: The cyclicality of separation and job-finding rates, by ability type

		Baseline		Alternative calibration	
		low a	high a	low a	high a
Separations	Average	0.0126	0.0075	0.0112	0.0065
	Cyclicality	**0.839**	**0.760**	**0.688**	**1.143**
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.631**	**-0.367**	**-0.510**	**-0.493**
Unemployment	Average	0.041	0.025	0.037	0.021
	Cyclicality	**1.109**	**0.822**	**0.879**	**1.212**

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cylicality is measured as in the CPS data (see notes in Table 1 for details). Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers.

generates higher average separation rates for the low-ability workers. However, the model does not well in capturing the cyclicality of separations as it generates a higher, not lower, cyclicality of separations for the low-ability types.

The reason for this failure is related to the cyclical behavior of the worker's outside option. The efficient-separation equation (12), rewritten for convenience, is

$$W_i(z, R_i(z)) + J_i(z, R_i(z)) = U_i(z),$$

where the left-hand side is the value of the match and the right-hand side is the value of the outside option. When aggregate labor productivity increases, the value of the match increases proportionally, whereas the value of being unemployed increases by less than one-for-one because b is constant over the business cycle. Therefore, staying employed becomes more attractive as aggregate productivity increases and thus R_i decreases. For workers with low ability the outside option fluctuates less as the constant term of U_i (the unemployment benefit b) is large relative to the non-constant term (the expected value next period) and thus R_i changes *more* in response to aggregate productivity shock. For this reason, separations are more cyclical for low-ability workers.

Table 3 also shows the results for an alternative calibration strategy where I assume that the unemployment benefit is proportional to worker ability ($b_i = ba_i$) and the variance of match productivity is higher for low-ability workers[12]. More precisely, I assume that σ_ε is twice as large for the low-ability group ($\sigma_\varepsilon^{high} = 0.02$; $\sigma_\varepsilon^{low} = 0.04$). In line with the data, this model generates higher average separation rates for the low-ability workers. More importantly, this model also generates a higher cyclicality of separation rates for the high-ability workers. The reason is that the density of matches with $x = R_i$ is higher for the low-variance (high-ability) group, and thus changes in the reservation match productivity translate into larger changes in the separation rate.[13]

This second calibration strategy generates both lower separations and higher cyclicality of separations for the high-wage group. However, it is unclear why the variance of match-specific productivity shocks should be higher for low-ability workers. One way of evaluating whether high-wage workers have lower variance of match productivity shocks is to look at the yearly wage changes between the two outgoing rotation groups of the CPS (in interviews 4 and 8). If one decomposes the log wage in the model into $w_i^a + w_{it}^x + w_t^z$, where w_i^a is a worker-specific effect, w_{it}^x a match-specific productivity effect and w_t^z an aggregate productivity effect, then we get that

$$d \log w_{it} = dw_{it}^x + dw_t^z.$$

Further, assuming that the distribution of match productivity shocks and aggregate shocks are constant over time and independent of each other, we get:

$$Var(d \log w_{it}) = 2Var(w_{it}^x)(1 - \rho_x) + 2Var(w_t^z)(1 - \rho_z),$$

where ρ_x and ρ_z are the autocorrelations of match-specific and aggregate productivity shocks. If the variance of match productivity shocks differs across wage groups, then we should observe

[12] This is essentially the calibration strategy used by Bils, Chang and Kim (2009). More precisely, they choose the variance of match specific productivities to match the average separation rate for each group.

[13] Formally, one can show that the change in the separation rate in response to aggregate productivity shocks is

$$\left.\frac{d \ln F(R_i)}{d \ln z}\right|_{z=1} = \frac{f_i(R_i)}{F_i(R_i)} \frac{dR_i}{dz},$$

where $\frac{f_i(R_i)}{F_i(R_i)}$ is the inverse Mills ratio for the empirical distribution of match productivity. Note that for many distributions and, in particular, for the (log) normal distribution the inverse Mill ratio is $\frac{f_i(R_i)}{F_i(R_i)}$ is decreasing in the variance of match productivities. Therefore, for a given $\frac{dR_i}{dz}$, the cyclicality of the separation rate is *decreasing* in the variance of match productivities.

Table 4. Wage dispersion by wage and education group

By wage group	sd(lw)	sd(dlw)
Below median	0.32	0.40
Above median	0.37	0.40

By education group	sd(lw)	sd(dlw)
HS degree or less	0.48	0.38
Some college or more	0.56	0.44

differences in the variance of wage changes. However, in the CPS data the variance of wage changes is very similar across the two wage groups. Table 4 shows that the standard deviation of the yearly wage growth rate is exactly the same across the two wage groups (and higher for those with some college education or more). To sum up, there seems to be little justification for assuming a higher variance of match productivity shocks for the *low*-ability group.

3.3 Other Types of Heterogeneity

Could other types of heterogeneity drive the patterns observed in the CPS data? To answer this question, I simulated the benchmark model above with different assumptions on the group-specific parameters.

1. Workers may differ in the utility derived from unemployment ($b_l < b_h$), but have the same ability ($a_l = a_h = 1$). With Nash-bargaining, workers with high b have higher wages as the value of their outside option is higher. This model generates more cyclical separations for the high-wage workers (high b), but counterfactually high average separation rates for high-wage workers. The reason is that those workers with a high b have a better outside option and thus separate at higher match productivities than those with a low b.

2. Workers may differ in their bargaining power ($\alpha_l < \alpha_h$) but have the same ability ($a_l = a_h = 1$). This model generates counterfactually high average separation rates, as well a counterfactually lower cyclicality of separations for high-wage workers (those with high bargaining power). The reason for the latter is that the outside option U_i fluctuates less for workers with low bargaining power and thus separations become much more attractive in recessions.

3.4 Wage Rigidity

How about other prospective explanations for the different cyclicality of separations of low and high-wage workers? One possible explanation is that wage rigidity leads to more cyclical separations for high-wage workers as the failure of adjusting the wage in response to an aggregate shock results in the firm firing the worker. The rigid-wage hypothesis, however, faces several difficulties in explaining the pattern in the CPS data. First, the wage observations in the CPS sample are 9-12 months prior to the the observed separation. Gottschalk (2005) shows that wages are usually renegotiated one year after the last change, which implies that for most records in my sample wages were renegotiated between interview 4 and the subsequent interviews 9-12 months later. Of course, it is possible that wages are renegotiated but still display substantial rigidity if the renegotiation results only in a small wage adjustment.

Second, wage rigidity does not necessarily lead to more cyclical separations for high-wage workers. In particular, if the contribution of match-specific productivity shocks x to the variance of total match productivity zxa_i is large, then it is very difficult to generate a model where wage rigidity leads to more cyclical separations for high-wage workers. If wages fail to adjust in response to match-specific productivity shocks, then high-wage workers should also be more likely to be fired in good times. In the data, aggregate shocks to labor productivtiy are rather small and, in particular, small compared to match-specific shocks. In my baseline calibration above, the standard deviation of match-specific shocks is 7.5 times higher than the standard deviation of aggregate shocks. Match-specific shocks are not observed but inferred from wage data, and reducing the standard deviation of match-specific productivity shocks would be at odds with data on cross-sectional wage dispersion.

Finally, sticky wages affect separations because wages fail to adjust when wages fall outside of the bargaining set (the range within which the surplus for both parties is positive). This implies that separations may occur even if the *joint* surplus is positive: when wages are too high, the firm fires the worker, whereas when wages are too low the worker quits. In both cases, however, the parties would be better off by renegotiating the wage and thus these separations are bilaterally inefficient. Another possibility would be to let wages adjust to the boundary of the bargaining set whenever they are about to leave it. In such a model, however, wage rigidity has little impact on separations as this type of wage rigidity affects how the suprlus is split, but has only a limited impact on the total surplus.[14] As long as separations occur only when the total surplus is negative – i.e., as long as separations are efficient –, the model is similar to a model with flexible wages and thus unlikely to explain the empirical patterns of separations I have documented in the CPS data

3.5 Firm and Plant Death

Another reason why separations are more cylical for workers with high ability could be that separations in recessions are driven by the death of firms and plants. In fact, there is ample evidence that firm and plant death is countercylical (see Davis, Haltiwanger and Schuh, 1996; Figura, 2006). If workers of different ability are randomly distributed across firms, then plant death will increase separations for workers of all types by the same absolute number, and more in percentage terms for those with low average separation rates (the high-ability workers). A simple way of modeling such shocks is to introduce an exogenous firm death shock. In the benchmark model with one employee per firm this is equivalent to an exogenous separation shock. Figura (2006) shows that the yearly plant death rate increased from bottom to peak by approximately 5 percentage points in the 1981/2 recession and by 7 percentage points in the 1991 recession. The average of these two recessions corresponds to an increase in the monthly death rate of approximately 0.5 percentage points. For this reason, I extend my benchmark model from above by assuming that firms are hit by a death shock (λ) with a 0.5% probability per month in recessions and with zero probability in booms. As expected, Table 5 shows that separations in this model are more cyclical but lower on average for high-ability workers, as in the CPS data. The models fails, however, to fully account for the differences in the cyclicality of separations between low- and high-ability workers. With firm and plant death shocks, differences in the cyclicality of separations only come from differences in the average separation rates. More precisely, one can show that in the presence of such shocks alone, the ratio of the cyclicality of separation rates is $\frac{\beta_{low}^{sep}}{\beta_{high}^{sep}} \approx \frac{\bar{s}_{high}}{\bar{s}_{low}}$ where $\bar{s}_i$ denotes the average separation rate of group i. The ratio of the average separation rates between the low- and high-wage workers in the CPS is 0.61,

[14] Wage rigidity of course may have an allocative role on hiring, as emphasized in a recent literature by Hall (2005), Hall and Milgrom (2008), van Rens et al. (2009) and others.

Table 5. Model with firm death shocks: The cyclicality of separation and job-finding rates

		λ shock only		λ and productivity shocks	
		low a	high a	low a	high a
Separations	Average	0.0153	0.0098	0.0151	0.0097
	Cyclicality	**0.892**	**1.300**	**0.826**	**1.144**
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.073**	**-0.045**	**-0.164**	**-0.114**
Unemployment	Average	0.048	0.032	0.048	0.031
	Cyclicality	**0.851**	**1.229**	**0.897**	**1.160**

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cylicality is measured as in the CPS data (see notes in Table 1 for details). Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers.

whereas the ratio of the cylicality of separation rates in the CPS is 0.53. In other words, a model with only firm and plant death shocks cannot fully explain the differences in cyclicality of separations in the CPS. As explained above, productivity shocks tend to shift separations in the opposite direction and thus make it even more difficult to fully match the differences found in the data.

4 Credit-Constraint Shocks

Recessions are often periods where access to credit becomes more difficult.[15] Because of a shortfall of productivity in the short term, firms might therefore be forced to close down projects that would be profitable in the long term. How does such a credit-tightening affect job separations? And, in particular, does it affect matches with workers of low and high ability in a different way?

To evaluate these questions more formally, I incorporate credit-constraint shocks into my benchmark model. I use a short-cut by assuming that in recessions worker-firm matches face a

[15] See, e.g., Lown and Morgan (2004) who provide evidence that banks strongly tighten commercial credit standards in recessions. Also, Kiyotaki and Moore (1997) provide a theoretical rationale for cyclical variations in borrowing constraints. In their model small aggregate shocks lead to tighter borrowing constraints through a price effect on collaterals. These effects on borrowing constraints can be large as a reduction in the price of the collateral can lead to a further decline in demand for these assets and thus to a further reduction in the value of the collateral.

constraint to produce cash flows above some negative number $\gamma(z)$:

$$zxa_i - w_i(z,x) \geq \gamma(z), \tag{13}$$

Of course, workers may be willing to deviate from the Nash bargained wage and take a wage cut in order to continue the relationship. For this reason, wages are assumed to satisfy the Nash-bargaining solution $w_i^{NB}(z,x)$ as long as the cash-flow constraint (13) can be met, but otherwise adjust to meet the constraint:

$$w_i(z,x) = \begin{cases} w_i^{NB}(z,x) & \text{if } zxa_i - w_i^{NB}(z,x) \geq \gamma(z) \\ zxa_i - \gamma(z) & \text{if } zxa_i - w_i^{NB}(z,x) < \gamma(z), \end{cases} \tag{14}$$

If the cash-flow constraint cannot be met at any acceptable wage for the worker, worker-firm matches will dissolve. The separation condition now states that worker and firm are willing to remain in the relationship if their share of the surplus is non-negative:

$$W_i(z, R_i^w(z)) - U_i(z) = 0 \tag{15}$$

$$J_i(z, R_i^f(z)) - V_i(z) = 0, \tag{16}$$

where $R_i^w(z)$ is the worker reservation match productivity and $R_i^f(z)$ is the firm reservation match productivity. By (15) and (16), the reservation match productivities differ between worker and firm and separations may occur even if the joint surplus is positive.[16] Actually, firms never unilaterally fire a worker since cash-flow constraints only impose an upper limit to the wage but not a lower limit (i.e. $R_i^w(z) \geq R_i^f(z)$).

If workers are willing to take wage cuts to continue the relationship, one may wonder whether cash-flow constraints will ever result in separations. One should keep in mind, however, that workers are willing to take wage cuts only as long as their share of the surplus remains positive. At the efficient-separation level of match productivity $R_i(z)$, for example, workers are not willing

[16] The assumption here is that wages are renegotiated every period. In fact, if the firm could commit to pay higher wages in the future when the constraint is no longer binding, the worker-firm match could always be sustained if the total current surplus is positive. It is, however, questionnable whether such commitment devices exist, especially, because it requires a state contingent path for future wages.

to take any wage cut because their surplus from the match is zero. Therefore, a binding cash-flow constraint will always lead to separation for those matches whose productivity is at, or below, the efficient-separation level of match productivity $R_i(z)$.[17] For worker-firm matches with $x > R_i(z)$ there is some room for wage adjustment. The actual wage cut that the worker may be willing to take is, however, small, because the surplus for those x close to $R_i(z)$ is small.

The value functions in this model extension are the same as in the baseline model, except for the value function of the filled vacancy:

$$J_i(z,x) = zxa_i - w_i(z,x) + \beta E \left[\begin{array}{c} \sigma_i^w(z',x') \max\{J_i(z',x'), V_i(z')\} \\ (1-\sigma_i^w(z',x'))V_i(z') \end{array} \middle| z, x \right], \tag{17}$$

where $\sigma_i^w(z',x')$ takes a value of 1 if the worker stays with the firm and 0 if the worker quits.[18]

4.1 Results

I use the same calibration as in the baseline model of Section 3. The only parameter left to calibrate is $\gamma(z)$. Table 6 shows the simulation results for three different values of $\gamma(z)$. I assume it to be either 100%, 250% or 400% of the average cash flow in the unconstrained economy (these values correspond to $\gamma(z) = -0.02$, $\gamma(z) = -0.05$ and $\gamma(z) = -0.08$ respectively). The average cash flow in this economy is about 2.0% of average labor productivity. This is similar to other models; e.g., the cash flow in the model of Shimer (2005) around 1.5% of average labor productivity. One may argue that these constraints are very tight as a firm would need just one to four months of average productivity (depending on the calibration of γ) to repay current losses. Note, however, that in this model match productivity shocks are highly correlated across time and thus the chances of recovering current losses are far smaller than that.

All my calibrations yield more cyclical separations for high-ability workers. The calibration with the tightest constraint ($\gamma(z) = -0.02$), however, seems unrealistic as it leads to aggregate separations that are far too cyclical relative to aggregate job findings. The reason is that the

[17] See Appendix A.2 for a formal proof of this statement.

[18] A directed search equilibrium is defined as $R_i^w(z)$, $R_i^f(z)$, $w_i(z,x)$, $\theta_i(z)$ and the value functions $U_i(z)$,$W_i(z,x)$,$V_i(z)$ and $J_i(z,x)$ that satisfy the: 1. Nash-bargaining solution subject to the cash-flow constraint (13), 2. separation equations (15) and (16), 3. zero-profit condition: $V_i(z) = 0$ and 4. value functions (7), (8), (9) and (17).

Table 6. Model with credit-constraint shocks: The cyclicality of separation and job-finding rates

		γ = -0.02		γ = -0.05		γ = -0.08	
		low a	high a	low a	high a	low a	high a
Separations	Average	0.0144	0.0091	0.0131	0.0084	0.0128	0.0077
	Cyclicality	**1.114**	**1.380**	**0.669**	**1.658**	**0.702**	**1.279**
Job findings	Average	0.30	0.30	0.30	0.30	0.30	0.30
	Cyclicality	**-0.025**	**-0.008**	**-0.205**	**-0.122**	**-0.397**	**-0.257**
Unemployment	Average	0.046	0.030	0.042	0.028	0.041	0.025
	Cyclicality	**0.916**	**1.133**	**0.690**	**1.477**	**0.847**	**1.246**

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cylicality is measured as in the CPS data (see notes in Table 1 for details). Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers.

constraint is relatively tight, which makes aggregate separations very volatile. The calibrations where $\gamma(z) = -0.05$ and $\gamma(z) = -0.08$ do better in that respect and, at the same time, produce more cyclical separations for high-ability workers. Quantitatively, the model even overpredicts the cyclicality for high-ability workers when $\gamma(z) = -0.05$, whereas it exactly matches the ratio of the cyclicality of separations of low- and high-ability workers in the CPS data when $\gamma(z) = -0.08$ (i.e. $\frac{\beta^{sep}_{low}}{\beta^{sep}_{high}} = 0.54$).

4.2 Discussion

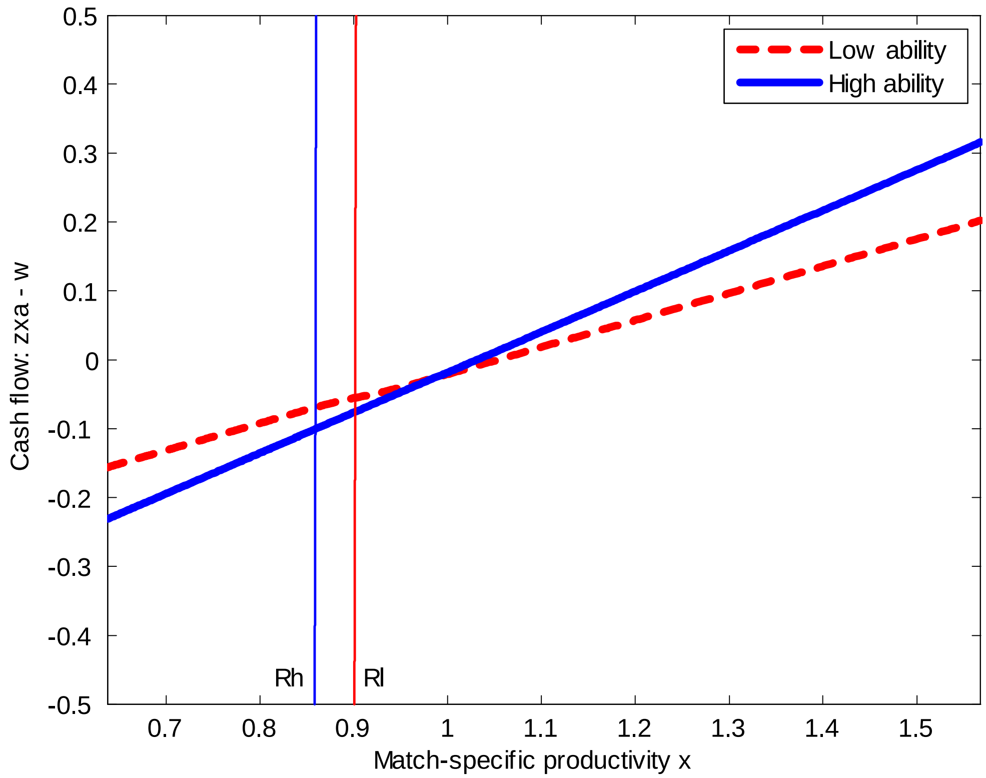
The important insight of this last model extension is that in the baseline model outlined in Section 3 each worker-firm match produces negative cash flows at the efficient reservation productivity level. As shown in Appendix A.2, the firm's cash flows at the reservation productivity level $R_i(z)$ can be written as:

$$CF_i(z, R_i(z)) = -\beta E\left[\max\left\{(1-\alpha)S_i(z', x'), 0\right\} \,\middle|\, z, R_i(z)\right], \tag{18}$$

This says that cash flows at the reservation productivity level $R_i(z)$ are equal to minus the expected future discounted match surpluses S_i (times the bargainig share of the firm). Therefore, as long as the firm receives a positive share of the surplus (i.e. $1-\alpha > 0$), cash flows are negative at $R_i(z)$. This can also be seen in Figure 6, which plots cash flows by match-specific productivity.

Importantly, cash flows are more negative at the reservation match productivity level for high-ability workers than for low-ability workers because the expected future surplus is higher.[19] For this reason, separations of high-ability workers are more sensitive to a tightening of credit.

Figure 6: *Cash flows by match-specific productivity and worker type*



One potential concern may be that, in the model, firms are small in the sense that they only have one employee. One may argue that if firms had more than one worker the above mechanism would produce different results because the cash-flow constraint would be operating at the firm and not at the match level. In particular, high-ability workers generate higher surplus for the firm (because of high expected future productivity) and thus the firm might prefer to lay off low-ability workers in order to keep its high-ability workers. Notice, however, that getting rid of

[19] This can be attributed to two effects: First, because high-ability workers face lower replacement rates, the reservation match productivity $R_i(z)$ is lower and thus cash flows more negative at $R_i(z)$. Second, match surpluses at a given level of x and z are increasing in ability, which implies that at $R_i(z)$ cash flows are more negative for high ability workers even if $R_i(z)$ is the same for both types (this can also be easily seen in Figure 6). Appendix A.2 shows that if both types of workers face identical replacement rates, then $S_i(z,x) = a_i\tilde{S}(z,x)$ where $\tilde{S}(z,x)$ is a function that is independent of ability type.

low-ability workers may not always relax the constraint enough to keep the high-ability workers. More generally, in a multi-worker firm, each worker-firm relationship has a shadow value of relaxing the cash-flow constraint. This shadow value is larger for matches with high-ability workers, because these workers produce more negative cash flows at the productivity threshold where separations occur. In other words, firing one high-ability worker would allow keeping many low-ability workers, whereas the firm would have to fire many low-ability workers to keep one high-ability worker. For reasonable assumptions regarding the substitutability between the two types of workers, one should therefore expect the mechanism in my model extension to be operative also in a multi-worker firm setup.

Ideally, one should set up a multi-worker firm model to investigate the qualitative and quantitative effects of cash-flow constraints on the cyclicality of separations for low- and high-ability workers. Such a model, however, is very complicated as the wage bargained by one worker affects the firm-level cash-flow constraint and thus, the wage bargained by other workers. Stole and Zwiebel's (1996) intrafirm bargaining game would be a good starting point, but further complicated by the presence of low- and high-ability types. This important work is left for future research.

5 Conclusion

This paper provides new facts about the composition of the unemployment pool over the U.S. business cycle. In recessions, the pool of unemployed shifts towards workers with high wages in their previous job. Moreover, this change is driven by the higher cyclicality of separations for high-wage workers. These empirical patterns are difficult to explain with a standard search-matching model with endogenous separations and worker heterogeneity, since it predicts shifts in the pool of unemployed in the opposite direction of the data.

I offer two extensions of the model that work better in replicating these new facts. The first extension introduces firm death shocks, which affect all workers indiscriminately of type. However, these shocks cannot fully account for the more cyclical separations of high-ability workers because, with such death shocks, differences in the cyclicality of separation rates between low-wage and high-wage individuals are limited by differences in the average separation rates between the two groups. The second extension with credit-constraint shocks, on the other hand, can fully match the differences in the cyclicality of separations between low- and high-ability workers. It is somewhat difficult to exactly pin down the magnitude of these credit-constraint shocks, but my simulations show that the separations of high-ability workers are more cyclical for a broad range of parameter values.

Shifts towards high-ability workers among the unemployed in slamps have important implications for models of aggregate fluctuations of the labor market and pose an additional challenge to the recent literature on the "unemployment volatility puzzle" (see Shimer, 2005). Specifically, these compositional changes aggravate the apparent lack of an amplification mechanism in the standard search-matching model, as they dampen the response of the firms' recruiting behavior to aggregate productivity shocks. Moreover, the shifts may have a large impact on the welfare costs of business cycles as high-ability workers are better able to self-insure against unemployment shocks (see, e.g., Mukoyama and Sahin, 2006). To conduct a proper welfare analysis, however, I have to model the savings and consumption choices of the employed and unemployed. I leave this important task for future research.

Another avenue for future research is to extend my empirical analysis with other data sources. Matched employer-employee data is particularly promising as it allows to determine the importance of firm death for separations. Moreover, it makes it possible to extract individual fixed effects from the wage and to perform the same type of analysis with the average individual effect instead of the average previous wage. It will also be interesting to extend my empirical analysis to other countries. Many European countries have extensive employment protection legislation, which may affect the sign as well as the magnitude of the shifts in the unemployment pool. E.g., seniority rules make it harder for firms to lay off more experienced workers. But it is unclear how these rules interact with the business cycle. On the one hand, seniority rules imply that separations in recessions should be concentrated on the less experienced workers. On the other hand, these rules might be circumvented or inapplicable in recessions (e.g., because of firm and plant death) and thus, the shift towards high-wage workers may be even stronger than in the U.S.

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Appendix

A.1 A Search-Matching Model with Non-Directed Search

If search on the firm side is non-directed to a particular worker type, then there is only one aggregate matching function:

$$M = \kappa u^{\eta} v^{1-\eta}. \tag{19}$$

Note that in this model there is an important interaction between the labor markets of low- and high-ability types, as the composition of the pool of unemployed matters for the firm's chances to meet the high-ability types and thus affects the incentives for posting vacancies.

The value functions of the worker are the same as before:

$$\begin{aligned} U_i(Z) &= b_i + \beta E\left[(1 - f(\theta_i))U_i(Z') + f(\theta_i)W_i(Z', \bar{x}) \middle| Z \right] && (20) \\ W_i(Z, x) &= w_i(Z, x) + \beta E\left[\max\left\{ W_i(Z', x'), U_i(Z') \right\} \middle| Z, x \right], && (21) \end{aligned}$$

whereas the value functions of the firm now are:

$$\begin{aligned} V(Z) &= -c + \beta E\left[(1 - q(\theta))V(Z') + q(\theta) \left(\begin{array}{c} \pi J_l(Z', \bar{x}) \\ +(1-\pi) J_h(Z', \bar{x}) \end{array} \right) \middle| Z \right] && (22) \\ J_i(Z, x) &= zxa_i - w_i(Z, x) + \beta E\left[\max\left\{ J_i(Z', x'), V(Z') \right\} \middle| Z, x \right], && (23) \end{aligned}$$

where the imporant difference is that the value of the vacancy now is independent of type, as firms post vacancies for all types of workers. This implies that the value of posting a vacancy depends on the share of the low-ability types in the pool of unemployed (π).

A *non-directed* search equilibrium is defined as $R_i(Z)$, $w_i(Z, x)$, $\theta(Z)$ and the value functions $U_i(Z)$,$W_i(Z, x)$,$V(Z)$ and $J_i(Z, x)$ that satisfy the: 1. Nash-bargaining solution (11), 2. efficient-separation equation (12), 3. zero-profit condition: $V(Z) = 0$ and 4. value functions (20), (21), (22) and (23).

Note that in the non-directed search equilibrium the unemployment rate for both groups, as well as the distribution of types across match productivities are aggregate state variables. The reason is that the firms' decision to post a vacancy depends on the share of low types in the pool of unemployed in the current as well as in future periods. The distribution of worker types across match productivties x is needed to forecast the share of low types in the future, because the more workers of one type are close to the productivity threshold where separations occur, the more likely the share will increase for that group in the future. This complicates the analysis considerably as it is generally not possible to solve a model with a highly dimensional state space such as with the distribution of worker types across match productivties. For this reason, I only do the comparative statitics for the non-directed search model because in the steady state the distribution of worker types is constant across time. I leave it for future work to compute an approximate equilibrium with a limited set of aggregate state variables similar to Krusell and Smith's (1998) method in models with heterogeneity in asset holdings. The Appendix Tables A.4, A.5 and A.6 show the comparative statics results for the directed and non-directed search model. The results between the two models are similar; in particular, the differences in the cyclicality of separations between the low- and high-ability types are not affected much by the modelling choices on non-directed or directed search.

A.2 A Search-Matching Model with Cash-Flow Constraints

This appendix provides formal propositions and proofs of the intuition explained in the text.

Proposition 1 *At the efficient reservation match productivity $R_i(z)$, the firm's cash flows are negative if the firm's bargaining share is larger than 0.*

Proof. At $R_i(z)$, the joint surplus of the match is zero, as well as the surplus share of the firm. Because of the zero-profit condition, we get:

$$\begin{aligned} 0 &= J_i(z, R(z)) - V_i(z) \\ &= J_i(z, R(z)) \\ &= CF_i(z, R(z)) + \beta E\left[\max\{J_i(z', x'), 0\} \,\middle|\, z, R_i(z) \right], \end{aligned}$$

and thus

$$\begin{aligned} CF_i(z, R_i(z)) &= -\beta E\left[\max\{J_i(z', x'), 0\} \,\middle|\, z, R_i(z) \right] \\ &= -\beta E\left[\max\{(1-\alpha) S_i(z', x'), 0\} \,\middle|\, z, R_i(z) \right], \end{aligned}$$

which says that cash flows have to be negative at the efficient reservation match productivity level if the firm expects a surplus from the match in the future, i.e., if the firm's surplus share is positive ($1 - \alpha > 0$). This holds for any process of match productivity with some positive probability of a higher match productivity in future periods. ■

Proposition 2 *At the efficient reservation match productivity $R_i(z)$, wages do not adjust in response to a credit-constraint shock, and matches separate if the constraint is binding.*

Proof. At the efficient reservation match productivity, the total match surplus as well as the worker share of the surplus is zero. Therefore, the worker is not willing to take a wage cut, because it would result in a negative surplus share for the worker. ■

Proposition 3 *If $b_i = ba_i$ and $f(\theta_i) = f$, then, at the efficient reservation match productivity $R_i(z)$, cash flows are more negative for high-ability workers.*

Proof. From the proposition above, we know that the cash flow at the reservation match productivity level depends on the discounted future expected surplus. So if the expected surplus is higher for high-ability workers, then cash flows are more negative at $R_i(z)$. If $b_i = ba_i$, then the surplus can be written as:

$$\begin{aligned} S_i(z,x) &= W_i(z,x) - U_i(z) + J_i(z,x) \\ &= a_i(zx - b) + \beta E\left[\max\left\{S_i(z',x'),0\right\}\middle|\, z,x\right] \\ &\quad -\beta f(\theta_i)\alpha E\left[\max\left\{S_i(z',\bar{x}),0\right\}\middle|\, z\right], \end{aligned}$$

and if $f(\theta_i) = f(\theta)$, then

$$S_i(z,x) = a_i\tilde{S}(z,x),$$

where $\tilde{S}(z,x) \geq 0$ is independent of ability. This implies that the surplus is increasing proportionally to ability and thus cash flows at $R_i(z)$ are more negative for high-ability workers. ■

It follows that, if $\frac{db_i}{da_i} = 0$, cash flows at the reservation match productivity level are even more negative for high-ability workers, since the surplus is even higher for high-ability workers. Note that the assumption that the job-finding rates are the same for the two groups is not necessarily met: the model calibration targets the average job-finding rate to be 0.3 for both groups, but the job-finding rates are allowed to differ over the cycle.

Appendix Tables

Table A.1 The cyclicality of separation rates, by wage group (robustness checks)

		Log(hourly wage)		Mincer residual	
		low	high	low	high
E--> U (Baseline)	**Cyclicality**	**0.40**	**0.75**	**0.45**	**0.67**
	(s.e.)	(0.082)***	(0.099)***	(0.063)***	(0.085)***
E --> U + OLF	**Cyclicality**	**0.05**	**0.30**	**0.10**	**0.21**
	(s.e.)	(0.043)	(0.055)***	(0.046)**	(0.056)***
E --> U (not on temporary layoff)	**Cyclicality**	**0.38**	**0.77**	**0.40**	**0.73**
(1988-2008 only)	(s.e.)	(0.086)***	(0.146)***	(0.096)***	(0.112)***
Subsample: age 25-54	**Cyclicality**	**0.43**	**0.75**	**0.46**	**0.73**
	(s.e.)	(0.089)***	(0.081)***	(0.072)***	(0.077)***
Subsample: men	**Cyclicality**	**0.46**	**0.74**	**0.50**	**0.73**
	(s.e.)	(0.080)***	(0.084)***	(0.064)***	(0.098)***
Subsample: full-time workers	**Cyclicality**	**0.38**	**0.74**	**0.44**	**0.67**
	(s.e.)	(0.088)***	(0.102)***	(0.066)***	(0.090)***
Subsample: Some college or more	**Cyclicality**	**0.42**	**0.74**	**0.45**	**0.76**
	(s.e.)	(0.121)***	(0.108)***	(0.100)***	(0.093)***
Subsample: 1990-2008	**Cyclicality**	**0.35**	**0.78**	**0.45**	**0.64**
	(s.e.)	(0.083)***	(0.111)***	(0.078)***	(0.110)***
Filtering: HP-filtered with smoothing parameter 14400	**Cyclicality**	**0.54**	**1.08**	**0.61**	**1.01**
	(s.e.)	(0.174)***	(0.171)***	(0.109)***	(0.200)***
Filtering: Not filtered, but controlling for linear trend	**Cyclicality**	**0.39**	**0.76**	**0.44**	**0.69**
	(s.e.)	(0.054)***	(0.068)***	(0.055)***	(0.062)***
Adjusted for time aggregation bias	**Cyclicality**	**0.28**	**0.61**	**0.32**	**0.54**
	(s.e.)	(0.084)***	(0.106)***	(0.069)***	(0.089)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000 (unless otherwise stated). The cylicality is measured as the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, job-finding or unemployment rate of group i at time t and Ut is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

Table A.2 The cyclicality of job-finding rates, by wage group (robustness checks)

		Log(hourly wage)		Mincer residual	
		low	high	low	high
U --> E (Baseline)	**Cyclicality**	**-0.57**	**-0.72**	**-0.68**	**-0.61**
	(s.e.)	(0.059)***	(0.069)***	(0.073)***	(0.077)***
U + OLF --> E	**Cyclicality**	**-0.38**	**-0.48**	**-0.41**	**-0.43**
	(s.e.)	(0.074)***	(0.060)***	(0.064)***	(0.060)***
U (not on temporary layoff) --> E	**Cyclicality**	**-0.62**	**-0.90**	**-0.76**	**-0.75**
(1988-2008 only)	(s.e.)	(0.067)***	(0.117)***	(0.094)***	(0.078)***
Subsample: age 25-54	**Cyclicality**	**-0.53**	**-0.69**	**-0.65**	**-0.59**
	(s.e.)	(0.084)***	(0.071)***	(0.099)***	(0.088)***
Subsample: men	**Cyclicality**	**-0.57**	**-0.66**	**-0.64**	**-0.61**
	(s.e.)	(0.067)***	(0.063)***	(0.091)***	(0.076)***
Subsample: full-time workers	**Cyclicality**	**-0.57**	**-0.69**	**-0.69**	**-0.58**
	(s.e.)	(0.078)***	(0.066)***	(0.100)***	(0.071)***
Subsample: Some college or more	**Cyclicality**	**-0.64**	**-0.73**	**-0.76**	**-0.62**
	(s.e.)	(0.085)***	(0.088)***	(0.078)***	(0.096)***
Subsample: 1990-2008	**Cyclicality**	**-0.60**	**-0.82**	**-0.75**	**-0.68**
	(s.e.)	(0.087)***	(0.088)***	(0.098)***	(0.079)***
Filtering: HP-filtered with smoothing parameter 14400	**Cyclicality**	**-0.65**	**-0.60**	**-0.68**	**-0.61**
	(s.e.)	(0.156)***	(0.136)***	(0.173)***	(0.159)***
Filtering: Not filtered, but controlling for linear trend	**Cyclicality**	**-0.69**	**-0.68**	**-0.76**	**-0.63**
	(s.e.)	(0.049)***	(0.058)***	(0.061)***	(0.048)***
Adjusted for time aggregation bias	**Cyclicality**	**-0.69**	**-0.86**	**-0.81**	**-0.74**
	(s.e.)	(0.072)***	(0.082)***	(0.087)***	(0.094)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000 (unless otherwise stated). The cylicality is measured as the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, job-finding or unemployment rate of group i at time t and Ut is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

Table A.3 The cyclicality of unemployment rates, by wage group (robustness checks)

		Log(hourly wage)		Mincer residual	
		low	high	low	high
U	**Cyclicality**	**0.81**	**1.25**	**0.91**	**1.11**
	(s.e.)	(0.024)***	(0.030)***	(0.027)***	(0.035)***
U + OLF	**Cyclicality**	**0.06**	**0.18**	**0.09**	**0.13**
	(s.e.)	(0.044)	(0.060)***	(0.047)*	(0.056)**
U not on temporary layoff	**Cyclicality**	**0.81**	**1.35**	**0.92**	**1.19**
(1988-2008 only)	(s.e.)	(0.048)***	(0.069)***	(0.056)***	(0.054)***
Subsample: age 25-54	**Cyclicality**	**0.80**	**1.24**	**0.91**	**1.11**
	(s.e.)	(0.024)***	(0.027)***	(0.031)***	(0.040)***
Subsample: men	**Cyclicality**	**0.78**	**1.18**	**0.88**	**1.14**
	(s.e.)	(0.032)***	(0.027)***	(0.032)***	(0.040)***
Subsample: full-time workers	**Cyclicality**	**0.80**	**1.21**	**0.92**	**1.09**
	(s.e.)	(0.027)***	(0.029)***	(0.028)***	(0.032)***
Subsample: Some college or more	**Cyclicality**	**0.81**	**1.16**	**0.95**	**1.07**
	(s.e.)	(0.045)***	(0.037)***	(0.035)***	(0.044)***
Subsample: 1990-2008	**Cyclicality**	**0.80**	**1.27**	**0.92**	**1.11**
	(s.e.)	(0.032)***	(0.045)***	(0.030)***	(0.039)***
Filtering: HP-filtered with smoothing parameter 14400	**Cyclicality**	**0.81**	**1.23**	**0.86**	**1.17**
	(s.e.)	(0.048)***	(0.060)***	(0.057)***	(0.076)***
Filtering: Not filtered, but controlling for linear trend	**Cyclicality**	**0.83**	**1.22**	**0.92**	**1.10**
	(s.e.)	(0.022)***	(0.028)***	(0.022)***	(0.028)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000 (unless otherwise stated). The cylicality is measured as the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, job-finding or unemployment rate of group i at time t and Ut is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

Table A.4 Comparative statics results: baseline calibration

		Non-directed search		*Directed search*	
		low a	high a	low a	high a
Separations	Average	0.0120	0.0073	0.0123	0.0073
	Cyclicality	**0.458**	**-0.242**	**0.288**	**-0.014**
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.807**	**-0.807**	**-0.988**	**-0.560**
Unemployment	Average	0.041	0.025	0.041	0.025
	Cyclicality	**1.265**	**0.565**	**1.277**	**0.546**

Table A.5 Comparative statics results: model with firm and plant death

		Non-directed search		*Directed search*	
		low a	high a	low a	high a
Separations	Average	0.0147	0.0097	0.0146	0.0095
	Cyclicality	**0.788**	**0.944**	**0.715**	**0.952**
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.151**	**-0.151**	**-0.225**	**-0.140**
Unemployment	Average	0.049	0.032	0.049	0.032
	Cyclicality	**0.939**	**1.094**	**0.940**	**1.092**

Table A.6 Comparative statics results: model with credit-constraint shocks (γ = -0.05)

		Non-directed search		*Directed search*	
		low a	high a	low a	high a
Separations	Average	0.0122	0.0081	0.0122	0.0082
	Cyclicality	**0.512**	**1.136**	**0.316**	**1.111**
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.240**	**-0.240**	**-0.446**	**-0.252**
Unemployment	Average	0.041	0.027	0.041	0.027
	Cyclicality	**0.752**	**1.376**	**0.761**	**1.363**