Separations, Sorting and Cyclical Unemployment*

Job Market Paper

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Abstract

Does the pool of unemployed sort towards low or high ability workers in recessions? I provide evidence with data from the Current Population Survey 1979-2008 that the composition of the pool of unemployed workers shifts towards those with high wages on their previous job. Moreover, I document that these cyclical 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 explaining these patterns, whereas an extension of the model with credit shocks does much better in accounting for these new facts. The reason is that, at the productivity threshold at which separations occur, matches with high ability workers produce more negative cash flows and thus separations of these workers are more sensitive to a tightening in the availability of credit.

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1 Introduction

This paper uncovers a new fact on the changes in the composition of the pool of unemployed over the U.S. business cycle. 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 on their previous job. These empirical patterns are robust to many different specifications; in particular, controlling for observable characteristics such as education, age, occupation etc. in the wage, I show that the share of unemployed with high residual wages increases in recessions, although the magnitude of the increase is smaller than for the raw wage measure. This suggests that both, observed as well as unobserved factors, explain the shift towards high wage workers in recessions. I also investigate whether these compositional shifts are due to differences in the cyclicality of separation or job finding rates across wage groups, and find that the compositional shifts are almost entirely driven by separations.

These empirical patterns appear to be in contradiction with findings from the 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. They demonstrate that with un-weighted wage data composition bias has almost no effect on the cyclicality of real wages, suggesting that the composition of the employed does not change over the business cycle but rather hours worked by skill group. Moreover, it is important to understand that changes in the composition of the employed do not necessarily translate into changes in the pool of the unemployed in the opposite direction. In fact, I show that a shift towards high wage workers in the pool of unemployed is fully consistent with no change in the composition of the pool of employed.

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

The second part of the paper tries to explain the documented facts. To that purpose, I 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 of the pool of unemployed towards low ability workers in recessions, which is inconsistent with the documented evidence. I also explore other calibrations of the model or models with different types of worker heterogeneities such as differences in bargaining power or home production, but all of these models have difficulties in replicating the key facts summarized above. I offer two extensions of the model that can explain the more cyclical nature of separations for high ability workers.

One explanation is that in a downturn many layoffs 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). To evaluate such a model, I include an exogenous aggregate separation shock in the model from above and find that indeed separations for high ability workers are more cyclical. The model, however, cannot fully explain the higher cyclicality of separations for high ability workers, because, with aggregate separation shocks, differences in the cyclicality of separation rates between low and high wage individuals are limited by differences in the average separation rates between these two groups.

Another extension of the model with credit shocks, where firms are constrained to pro-

[1] I use a simplified version of Bils et al. (2009), who study the cylicality 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 for a discussion of their empirical results from the Survey of Income and Program Participation (SIPP).

duce positive cash flows in recessions, also produces more cyclical separations for high ability workers. The idea is that in recessions it is more difficult to obtain outside financing as liquidity dries up in financial markets. The important insight is that in the baseline model with efficient separations, worker-firm matches produce negative cash flows at the productivity threshold at which separations occur. The firm is willing to pay the worker above current match productivity as it is compensated by expected positive future cash flows. Thus if in recessions firms face constraints on their cash flows, 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 more negative cash flows at the efficient (unconstrained) separation threshold and thus separations of these workers are more sensitive to a tightening in the availability of credit. Therefore, the model produces more cyclical separations for high ability workers, consistent with the documented empirical patterns in the CPS 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 and discusses alternative calibration strategies. Section 4 extends the model with credit shocks, and Section 5 concludes.

2 Data

I use 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 of age 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. Figure 1 shows the panel structure of the survey in more detail. Note that the CPS records the labor force status for each person in the sample each month. Weekly hours and earnings, however, are only in the fourth and eighth interview of the survey, referred to as the Outgoing Rotation Groups (ORG).

2.1 Sample criteria and measurement issues

As outlined in the introduction, I' m interested in the cyclicality of separations and hirings for different wage groups. 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 only and analyse the separation and job finding rates in subsequent months. I do not include individuals with 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 and exlude individuals with a wage above the 99.75th or below the 0.25th each year and individuals with weekly hours below 5 or above 80. The sample size is 1,369,741 individuals and for each individual there are up to 3 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 subsequent interviews 9,10, 11 and 12 months later (remember there is a gap of 8 months between the 4th and the 5th interview): The fraction of matches between the fourth interview and the inteviews 5-8 was 0.73 (in other words, there were 27% individuals with no match between interview 4 and the 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

[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.

logit regression. This inflates the weight for groups and years with high attrition rates.[4]

Another issue that arises is that 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 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 criterium 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 of unemployment. Of course, it is still possible that movements in- and out of the labor force are cyclical across groups and that the differential cyclicality cancels 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 ommitted here from the analysis.

2.2 The cyclicality of the wage of joblosers

Does the composition of the pool of unemployed change over the business cycle? In particular, are there changes in the pool in terms of ability? In Figure 2 I use the CPS data and plot 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

[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.

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

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). Figure 3 shows that when I remove year effects the average wage for the unemployed is even more closely correlated with the unemployment rate, with a correlation coefficient of 0.72.[6] This evidence indicates that in a recession the composition of the pool shifts towards high wage workers. Figure 4 shows the same plot but for the residual of a regression of the wage on observable characteristics such as age, gender, marital status, education and race, and dummies for industry, occupation and year.[7] 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 of Figure 2. This suggests that both observed and unobserved factors contribute to the cyclical behavior of the wage of joblosers.

One thing to keep in mind is that the reported series are hp-filtered and thus the mean is zero for both the employed and unemployed over the entire sample period. The mean of the unfiltered series is, however, considerably lower for those who lose their job over the next year as opposed to those who remain employed. If wages reflect worker ability, 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 that wage compression drives the pattern 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 claim, I attribute a wage rank to each individual in my data set, which I define as the rank in the wage distribution in a given year if one lined up all individuals according to their current wage from the lowest to the highest. If wage compression drives the patterns

[6] 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.

[7] The equation was estimated for 5-year intervals, to allow for changes in the estimated coefficients over the 30 year sample period.

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 the patterns documented above.[8] In terms of the magnitude, a percentage point increase in the unemployment rate leads to a 1.5 percentage point increase in the average wage rank of the joblosers, 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 either arise because of different behavior of inflows into or the outflows from unemployment (or both). For this reason, I analyze in more detail the worker *flow* data from my CPS sample to determine whether the patterns documented in the previous section are due to the job separation or the job finding margin. In particular, I devide 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 both 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 U to E). The groups are devided into below or above the median wage in interview 4 and the transitions are analysed for subsequent interviews (i.e. transitions between interviews 5 to 6, 6 to 7 and 7 to 8).

2.3.1 Measurement

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

$$du_t \approx u_t(1-u_t)\left[d\ln s_t - d\ln f_t\right]$$

[8] The correlation coefficient is 0.70 if I use the median wage rank instead.

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

$$\phi_{it}^{U}=\psi_{i}^{U}\frac{u_{it}}{u_{t}}$$

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). One can show that the share of group i in the pool can be decomposed into

$$d\phi_{it}^{U}\approx\phi_{it}^{U}\left(\begin{array}{c}(1-u_{it})\left[d\ln s_{it}-d\ln f_{it}\right]\\ -(1-u_{t})\left[d\ln s_{t}-d\ln f_{t}\right]\end{array}\right)$$

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. To understand how separations and job findings relate to cyclical changes in the unemployment rate, one 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:

$$\ln x_{it}=\alpha_{i}+\beta_{i}\ln U_{t}+\varepsilon_{it}$$

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). All series are monthly and are seasonally adjusted and detrended with an hp-filter with smoothing parameter 900,000.

2.3.2 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, on average, separations are lower for high wage workers than for low wage workers. 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 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.

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.

2.3.3 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.

2.4 Relation to previous research

Bils et al. (2009) find similar evidence of low-wage vs. high-wage workers in the data from the Survey of Income and Program Participation (SIPP), but pay little attention to the question of cyclical changes in the composition of the pool of unemployed. They split their sample into four groups: low and high hours, and low and 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 they 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.[9][10]

Solon, Barsky and Parker (1994) show that there is a substantial composition bias when looking at the cyclicality of aggregate real wages. The empoyed 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,

[9] 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).

[10] 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).

because it suggests that the proportion of high-wage workers *among the employed* increases in a recession. 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) showed 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 the composition of the employed does not change over the business cycle but rather hours worked by skill group.

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 employed to the unemployed, improves the quality of both pools if he or she is below the median ability in the pool of employed but above the median ability in the pool of unemployed. 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:

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

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 abiltiy 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 (1) to compute the implied change in the share in the pool of employed. The results are as follows:

$$\begin{aligned}\frac{d\phi^U_{low,t}}{dU_t} &\approx -1.98\\ \frac{d\phi^E_{low,t}}{dU_t} &\approx -0.05\end{aligned}$$

which says that the share of the low ability types decreases by almost two percentage points in response to a one percentage point increase in the aggregate unemployment rate, whereas the composition of the pool of employed stays nearly constant. This is consistent with Hines, Hoynes and Krueger (2001) who found that composition bias is not important in the cyclicality of aggregate real wages (see above).

3 Model

I setup a search-matching model with endogenous separations and worker heterogeneity in terms of ability. I rely on a simplified version of Bils et al. (2009) and discuss different calibrations and extensions, in order to see how worker heterogeneity could explain the compositional changes in the pool of unemployed.

There are two types of workers who differ in their market productivity a and potentially other parameters. There is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function:

$$M_{it} = \kappa u_{it}^{\eta} v_{it}^{1-\eta}$$

Search on the firm side is assumed to be directed. This implies that labor markets are segmented as in Bils et al. (2009). Unemployed workers search for work in a particular market and are matched with firms according to the matching function:

$$M_{it} = \kappa u_{it}^{\eta} v_{it}^{1-\eta}$$

where u_{it} is the unemployment rate of group i at time t and v_{it} the vacancy rate. This implies that job finding probability $p(\theta_{it}) = \frac{M_{it}}{u_{it}}$ and the hiring rate $q(\theta_{it}) = \frac{M_{it}}{v_{it}}$ are group specific.

Match productivity is defined as zxa where z is aggregate productivity, x match specific productivity and a worker specific productivity. Match specific productivity is assumed to follow an AR(1) process as discussed below in the calibration strategy.

Now, let's proceed to describe the value functions of the workers and firms. The value function of the unemployed worker is:

$$U_i\left(z\right) = b_i + \beta E\left[(1 - f(\theta_i))U_i(z') + f(\theta_i)W_i(z', \bar{x}) \middle| \, z\right] \tag{2}$$

where Z is the set of aggregate state variables. Note that in the case of non-directed search the job finding probability is not worker type specific and reduces to $f(\theta)$. The value of being unemployed depends on the unemployment benefit b_i, which potentially depends on worker type, and the discounted future value of being unemployed or having a job with value W_i. Note that I assume that all matches start at the median match productivity $\bar{x}$.

The value function of the employed worker is:

$$W_i(z, x) = w_i(z, x) + \beta E\left[\max\left\{W_i(z', x'), U_i(z')\right\} \middle| \, z, x\right] \tag{3}$$

which depends on the utility from the current wage and the discounted future value. Whenever the value of the job W_i is lower then the value of being Unemployed U_i, the worker will quit the job.

The value of posting a vacancy for a firm is:

$$V_i(z) = -c_i + \beta E\left[(1 - q(\theta_i))V_i(z') + q(\theta_i)J_i(z, \bar{x}) \middle| \, z\right] \tag{4}$$

which depends on the current vacancy posting cost c_i and some discounted future 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:

$$J_i(z,x) = zxa_i - w_i(z,x) + \beta E\left[\ \max\left\{J_i(z',x'), V_i(z')\right\}\ \middle|\, z,x\right] \tag{5}$$

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

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

$$[W_i(z,x) - U_i(z)] = \frac{\alpha}{1-\alpha}\left[J_i(z,x) - V_i(z)\right] \tag{6}$$

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 x below which the employment relationship is dissolved, satisfies:

$$S_i(z, R_i(z)) = 0 \tag{7}$$

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

The directed search equilibrium then is defined as $R_i(z)$, $w_i(z,x)$, θ_i and the value functions $U_i(z)$,$W_i(z,x)$,$V_i(z)$ and $J_i(z,x)$ that satisfy: 1. The Nash bargainin solution (6), 2. The efficient separation equation (7), 3. The zero profit condition: $V_i(z) = 0$ and 4. The value functions (2), (3), (4) and (5).

3.1 Calibration

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

Parameter	**Parameter name**	**Source/Target**
$\beta = 0.9966$	Discount factor	$r = 4.17\%$
$f(\theta) = \kappa\theta^{\eta}; \eta = 0.5; \kappa = 0.3$	Matching function	$f(\theta) = 0.3$; Micro studies
$\alpha = 0.5$	Worker's barg. power	Hosios condition
$c_{high}= 0.64/c_{low}= 0.20$	Vacancy posting cost	Monthly job finding rate=0.3
$b = 0.6$	Unemployment benefit	Shimer (2005);HM (2008)
$\ln x_{t+1}= 0.98 \ln x_t+\epsilon_t$	Match specific prod.	Bils et al. (2009)
$\sigma_\epsilon= 0.03$	Std of shocks to x	Monthly sep. 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=2y
$a_{high}/a_{low}= 1.2/0.8$	Ratio of worker productivity	CPS data

The parameters are chosen for both groups of workers unless otherwise noted. The elasticity of the matching function η is chosen in accordance with estimates from micro studies and set to 0.5. The worker's bargaining power is set equal to the elasticity of the matching function in order to satisfy the Hosios condition. The vacancy posting cost c_i is set to match a monthly job finding rate of 0.3 as in the CPS data. The log of match productivity is assumed to follow an AR process with autocorrelation 0.98 and the standard deviation of match prodocutivity 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 the Tauchen's (1986) algorithm. Aggregate productivity is assumed to take 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 assumption 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., for example, 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 Baseline

Table 3 reports the results for the baseline calibration. The same filtering methods were applied to the simulated time series as for the empirical results from the CPS. I also report the steady state elasticities for the directed as well as for the non-directed search model. The Table 3 shows that the model generates higher average separation rates for the low ability workers. The reason is that the surplus from a relationship is lower for low ability people and thus they separate at a higher level of match productivities x. However, the model does not well in capturing the cyclicality of separations as it generates a higher cyclicality of separations for the low ability types.

The reason is related to the cyclical behavior of the worker's outside option. The efficient separation equation (7), here rewritten for convenience, is

$$W_i(z,x) + J_i(z,x) = U_i(z) \tag{8}$$

where the left-hand side is value of the match and the right-hand side the value of the outside option. When aggregate labor productivity increases, the value of being employed increases proportionally, whereas the value of being unemployed increases by less than one-to-one. The reason is that b is constant over the business cycle. Therefore, staying employed becomes more attractive as aggregate productivity increases and separations occur less frequently (i.e. R is lower). For worker's with low ability the outside option fluctuates less as the constant term b is large relative to the non-constant term (the expected value next period). As a consequence, low ability workers change the reservation match productivity R_{low} *more* in response to a positive aggregate productivity shock and thus separations are more cyclical for these workers.

Table 3 also shows the results for an alternative calibrations strategy[11] 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. More precisely, I assumed that σ_ϵ is twice as large for the low ability group ($\sigma_\epsilon^{high} = 0.02; \sigma_\epsilon^{low} = 0.04$). 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. 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 Mill 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.

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 (interviews 4 and 8). If one decomposes the log wage in the model into $a_i + x_{it} + z_t$, where a_i is an individual worker effect, x_{it} a match productivity effect and z_t an aggregate productivity effect, then

[11] This is essentially the calibration strategy used by Bils et al. (2009).

we get that

$$d \log w_{it} = dx_{it} + dz_t$$

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

$$Var(d \log w_{it}) = 2Var(x_{it})(1 - \rho_x) + 2Var(z_t)(1 - \rho_z)$$

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 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 heterogeneities

Could other types of heterogeneities drive the patterns observed in the CPS data? I discuss two types heterogeneities:

1. Workers 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 the 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 differ in their bargaining power ($\alpha_l < \alpha_h$) but have the same ability ($a_l = a_h = 1$): In this model workers with high bargaining power have higher wages. This model

generates both counterfactually high average separation rates as well a counterfactually lower cyclicality of separations for high wage workers. The reason for the latter is that the outside option fluctuates less for a worker with low bargaining power (with $\alpha = 0$, e.g., the value of being unemployed is constant over the business cycle) and thus separation into unemployment becomes much more attractive in a recession.

3.4 Wage rigidity

Are there other explanations for the different cyclicality of separations of low and high 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 shocks results in the firm firing the worker. The rigid wage hypothesis, however, faces several difficulties in explaining the pattern in the CPS data for several reasons. 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 is large, then it is very difficult to generate a model where wage rigidity leads to more cyclical separations for high wage workers. The reason is that 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 economic times. Note that, in the data, aggregate shocks to labor productivtiy are rather small and, in particular, they are small compared to match specific shocks. In my baseline calibration from above, the standard deviation of match specific shocks is 7.5 times higher than the standard deviation of aggregate shocks. Of course, 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 margin of the bargaining set whenever they are about to leave the bargaining set. In such a model, however, wage rigidity has little impact on separations as this type of wage rigidity simply affects how the suprlus is split, but has only a limited impact on the total surplus.[12] As long as separations thus 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 it is unlikely to explain the empirical patterns of separations documented with the CPS data

3.5 Firm and plant death

One possibility 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 introducing such firm level shocks into the model is by introducing an exogenous firm death shock, which in this model with one employee per firm 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 both recessions corresponds to an increase in the monthly death rate of approximately 0.5 percentage point. For this

[12] 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.

reason, I extend my model from above by assuming that in a recessions firms are hit by a death shock with a 0.5% probability per month and with zero probabiliy in a boom. 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. The reason is that with firm and plant death shocks, separations increase to the same extent in absolute terms and, therefore, differences in the cyclicality of separations only come from differences in the average separation rates. The ratio of the average separation rates between the low and high wage workers in Table 1 is 0.62, whereas the ratio of the cylicality of separation rates between these two groups is 0.53. To fully explain the patterns in the CPS, one thus requires a model with an aggregate shock that hits high ability workers more strongly than low ability workers.

4 Credit shocks

Recessions are often periods were access to credit becomes more difficult.[13] Because of a temporary shortfall in productivity, 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 this idea more formally, I incorporate credit shocks into the model from above. In particular, I assume that in recessions worker-firm matches face a constraint to produce cash flows above some negative number $\gamma(z)$:

$$zxa_i - w_i \geq \gamma(z) \tag{9}$$

[13] 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.

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 (9) can be met, but otherwise adjust to meet the constraint:

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

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:

$$W_i(z, R_i^w(z)) - U_i(z) = 0 \tag{10}$$

$$J_i(z, R_i^f(z)) - V_i(z) = 0 \tag{11}$$

where $R_i^w(z)$ is the worker reservation match productivity and $R_i^f(z)$ is the firm reservation match productivity. Note that the reservation match productivities now differ between worker and firm and separations may occur even if the joint surplus is positive.[14] 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, for example, workers are not willing 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 the

[14] 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.

efficient separation level $R_i(z)$.[15] 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 of this model extension are the same as in the baseline model, except for the value function of the filled vacancy:

$$J_i(z,x) = zxa_i - w_i(z,x) + \beta E\left[\begin{array}{c} \sigma_i^w(z',x')\max\{J_i(z',x'),V_i(z')\} \\ (1-\sigma_i^w(z',x'))V_i(z') \end{array}\middle| z,x\right] \tag{12}$$

where $\sigma_i^w(z',x')$ takes the value of 1 if the worker stays with firm and 0 if the worker quits.[16]

4.1 Results and discussion

I use the same calibration as the baseline model in Section 3. The only parameter left to calibrate is $\gamma(z)$. Table 6 shows the results of the simulations for two values of $\gamma(z)$. I assume it to be either 2% or 5% of average labor productivity. Both calibrations yield more cyclical separations for high ability workers. The calibration with the more tight constraint, however, produces separations that are far too cyclical relative to job findings as too many matches are affected by the constraint in recessions. The calibration where $\gamma(z) = -0.05$ does better in that respect and at the same produces much more cyclical separations for high ability workers. Quantitatively, in some sense, the model does too well as separations for the high ability workers are up to three times as cyclical as separations for the low ability workers, whereas the ratio is just below two in the CPS data.

The important insight 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 Figure 6. As shown in the Appendix A, the firm's cash flows at the reservation productivity

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

[16] The directed search equilibrium is defined as $R_i^w(z)$, $R_i^f(z)$, $w_i(z,x)$, θ_i and the value functions $U_i(z)$,$W_i(z,x)$,$V_i(z)$ and $J_i(z,x)$ that satisfy: 1. The Nash bargaining solution subject to the cash flow constraint (**??**), 2. The separation equations (10) and (11), 3. The zero profit condition: $V_i(z) = 0$ and 4. The value functions (2), (3), (4) and (12).

level $R_i(z)$ can be written as:

$$CF_i(z, R_i(z)) = -\beta E\left[\ \max\{(1-\alpha)S_i(z', x'), 0\}\ \middle|\, z, R_i(z)\right] \tag{13}$$

which 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 $R_i(z)$. Importantly, cash flows are more negative at the reservation match productivity level for high ability workers because the expected future surplus is higher.[17] For this reason, separations of high ability workers are more sensitive to a tightening in the availability of credit.

One potential concern with this model is that firms are small in the sense that they only have one employee. One may be worried that if one set up a model with 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 high ability workers. Notice, however, that getting rid of low ability workers might 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 separation margin. 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 these reasons, one should expect the mechanism presented above to be operative also in a multi-worker firm setup.[18]

[17] This can be attributed to two effects: First, because high ability workers face lower replacement rates, the reservation match productivity is $R_i(z)$ is lower and thus cash flows more negative at the separation margin $R_i(z)$. Second, match surpluses at a given level of x and z are increasing in ability, which implies that at the separation margin 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 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.

[18] Ideally, one should set up a multi-worker firm model to investigate the qualitative and quantitative effects

5 Conclusion

This paper provides new evidence on the changes in the composition of the pool of unemployed over the U.S. business cycle. Using longitudinal micro-data from the Current Population Survey (CPS) 1979-2008, I show that in recessions the pool of unemployed shifts towards workers with high wages on their previous job. Moreover, I document that these shifts are almost entirely driven by differences in the cyclicality of separations between low and high wage workers rather than by differences in the cyclicality of job findings.

These empirical patterns are difficult to explain with a search-matching model with endogenous separations and worker heterogeneity, as it predicts shifts in the pool of unemployed in the opposite direction of the data. I also investigate whether other explanations such as other types of heterogeneities or wage rigidity could drive the documented empirical patterns, but find that these explanations either do not match the documented facts or require unrealistic assumptions on certain parameters of the model.

A model with firm and plant death shocks works better in the sense that it produces shifts towards high wage workers in recession. However, it cannot fully reproduce the differences in the cyclicality of separations between low and high ability types, as differences in the cyclicality are limited by the differences in the average separation rates. Credit shocks, on the other hand, can fully match the differences in the cyclicality of separation rates between these two groups of workers, because they affect high ability workers more strongly. The intuition is that high ability workers produce more negative cash flows at the productivity threshold at which separations occur, and thus separations of these workers are more sensitive to a tightening in the availability of credit.

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 presences of low and high ability worker types. This important work is left for the future.

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Appendix A. A search-matching model with endogenous separations and cash flow constraints

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

Proposition 1 *At the separation margin, the firm's cash flows are negative if the firm's bargaining share is larger than 0.*

Proof. At the separation margin, 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 separation level whenever the firm expects a surplus from the match in the future. This holds 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 separation margin, wages do not adjust, and a binding cash flow constraint leads to separation.*

Proof. At the separation margin, 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 reservation match productivity level $R_i(z)$ 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 $\frac{db_i}{da_i} < 1$, cash flows at the separation margin are even more negative for high ability workers, since surplus are even more strongly increasing in worker ability. Note that the job finding rates for the two groups are not necessarily the same, but the data presented in Section 2 show that the average as well as the cyclicality of job finding rates are very similar for low and high wage workers. The model calibration targets the average job finding rate to be 0.3 for both groups and thus the assumption that $f(\theta_i) = f(\theta)$ is met on average, though they are allowed to differ over the cycle.

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

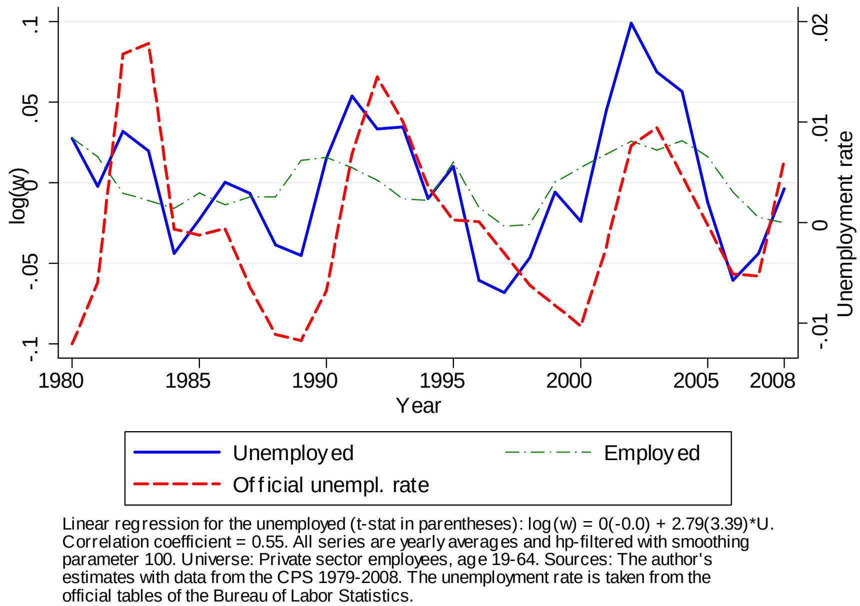


Figure 2: *Average wage from previous year by employment status.*

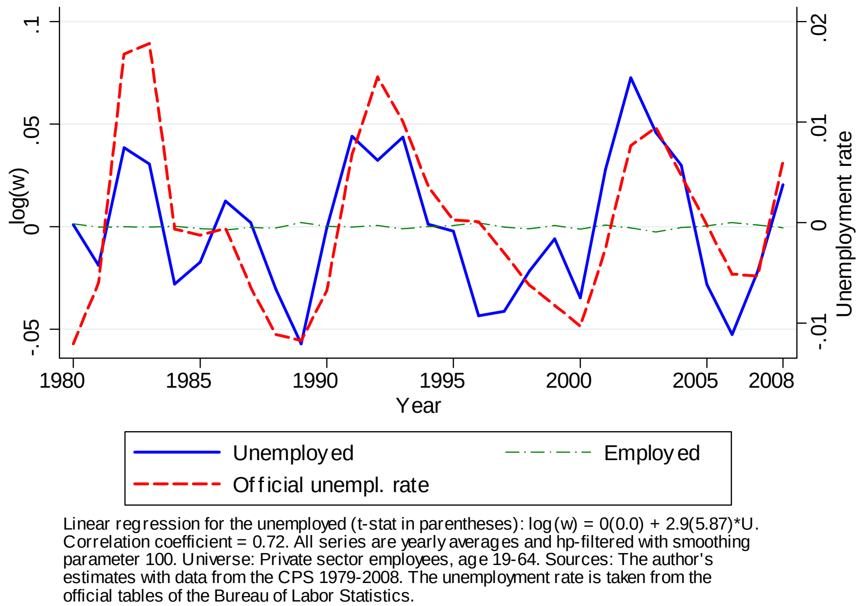


Figure 3: *Average wage from previous year by employment status (residuals from a regression of the log wage on year dummies).*

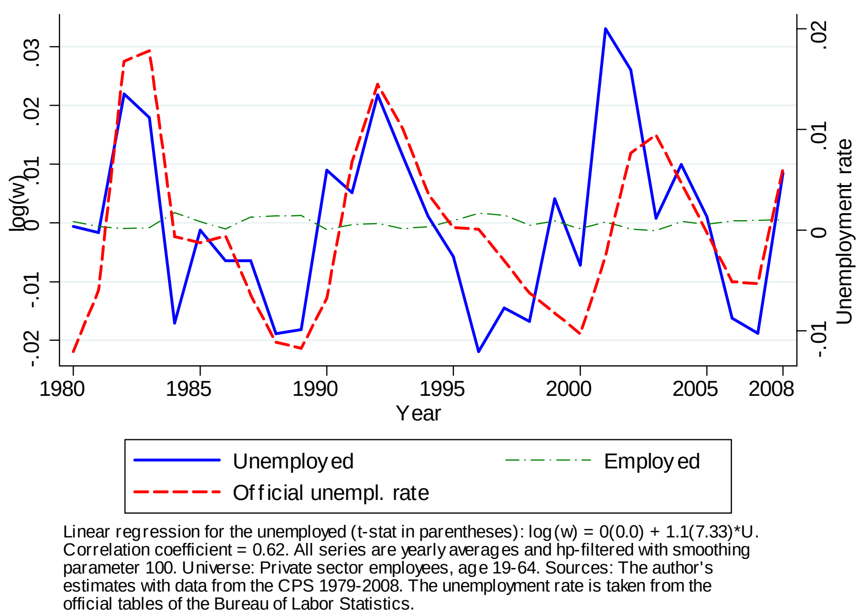
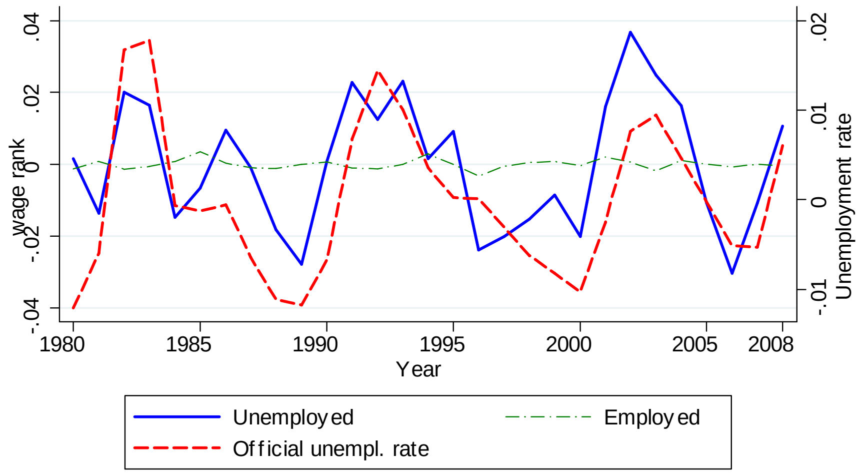


Figure 4: *Average wage from previous year by employment status (residuals from a regression of the log wage on observable characteristics and dummies for state, year, occupation and industry).*



Linear regression for the unemployed (t-stat in parentheses): rank= 0(0.0) + 1.54(5.93)*U.
Correlation coefficient = 0.72. The wage rank is defined as the individual position in the
wage distribution in a given year devided by the total number of observations in that year.
All series are yearly averages and hp-filtered with smoothing parameter 100.
Universe: Private sector employees, age 19-64. Sources: The author's estimates
with data from the CPS 1979-2008. The unemployment rate is taken from the
official tables of the Bureau of Labor Statistics.

Figure 5: *Average wage rank by employment status.*

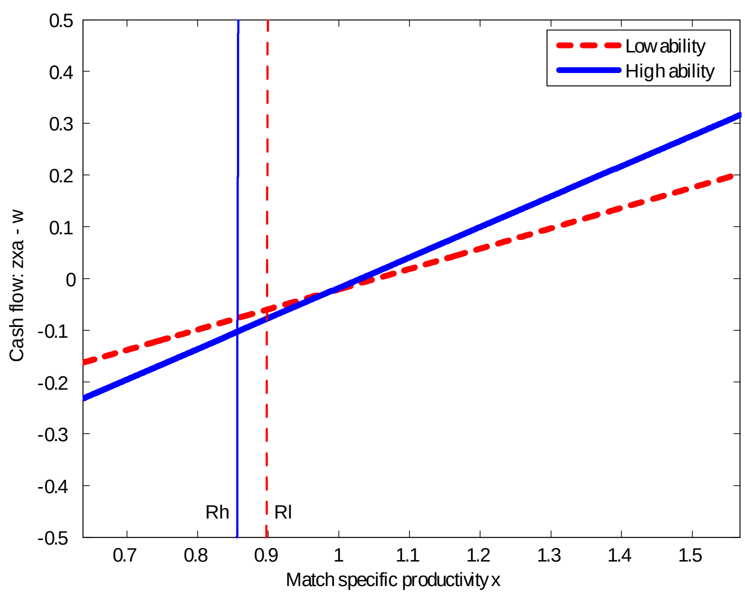


Figure 6: *Cash Flows by worker type and match specific productivity*

Table 1. CPS 979-2008: Average and cyclicality of separation and hiring rates, by wage group

		Log(hourly wage)		Mincer residual	
		low	*high*	*low*	*high*
Separations (E --> U)	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 (U --> E)	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 (U)	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, hiring 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 2. CPS 1994-2008: Average and 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%. 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, hiring 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: 166 monthly observations. Source: The author's estimates with data from the Current Population Survey 1994-2008.

Table 3. Baseline model: Average and cyclicality of separation and hiring rates, by ability type

		Baseline low a	*Baseline* high a	*Alternative calibration* low a	*Alternative calibration* high a
Separations (E --> U)	Average	0.0126	0.0075	0.0112	0.0065
	Cyclicality	**0.839**	**0.760**	**0.688**	**1.143**
Job findings (U --> E)	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.631**	**-0.367**	**-0.510**	**-0.493**
Unemployment (U)	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 the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, hiring or unemployment rate of group i at time t and Ut is the sample unemployment rate. Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers. For the steady state comparisons, the cyclicality is measured as dlog(xit)/dlog(Ut).

Table 4. Wage dispersion by wage and education group

	sd(lw)	sd(dlw)
By wage group		
Below median	0.32	**0.40**
Above median	0.37	**0.40**
By education group		
HS degree or less	0.48	0.38
Some college or more	0.56	0.44

Table 5. Model with firm death shocks: Average and cyclicality of separation and hiring rates

		λ shock only low a	*λ shock only* high a	**λ and productivity *shocks*** low a	**λ and productivity *shocks*** high a
Separations (E --> U)	Average	0.0153	0.0098	0.0151	0.0097
	Cyclicality	**0.892**	**1.300**	**0.826**	**1.144**
Job findings (U --> E)	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.073**	**-0.045**	**-0.164**	**-0.114**
Unemployment (U)	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 the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, hiring or unemployment rate of group i at time t and Ut is the sample unemployment rate. Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers. For the steady state comparisons, the cyclicality is measured as dlog(xit)/dlog(Ut).

Table 6. Model with credit shocks: Average and cyclicality of separation and hiring rates

		γ=-0.02		γ=-0.05	
		low a	**high a**	**low a**	**high a**
Separations (E --> U)	Average	0.0144	0.0091	0.0131	0.0084
	Cyclicality	**1.11**	**1.38**	**0.669**	**1.658**
Job findings (U --> E)	Average	0.30	0.30	0.30	0.30
	Cyclicality	**-0.03**	**-0.01**	**-0.205**	**-0.122**
Unemployment (U)	Average	0.046	0.030	0.042	0.028
	Cyclicality	**0.92**	**1.13**	**0.690**	**1.477**

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cylicality is measured as the coefficient β in the regression log(xit) = α+βlog(Ut)+εit, where xit is the separation, hiring or unemployment rate of group i at time t and Ut is the sample unemployment rate. Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers. For the steady state comparisons, the cyclicality is measured as dlog(xit)/dlog(Ut).

Appendix

Table A.1. CPS 1979-2008: Cyclicality of separation rates, by wage group (Robustness checks)

		Log(hourly wage)		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	**Cyclicality**	**0.54**	**1.08**	**0.61**	**1.01**
smoothing parameter 14400	(s.e.)	(0.174)***	(0.171)***	(0.109)***	(0.200)***
Filtering: Not filtered, but	**Cyclicality**	**0.39**	**0.76**	**0.44**	**0.69**
controlling for linear trend	(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 $\log(x_{it}) = \alpha+\beta\log(U_t)+\varepsilon_{it}$, where x_{it} is the separation, hiring or unemployment rate of group i at time t and U_t 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. CPS 1979-2008: Cyclicality of hiring rates, by wage group (Robustness checks)

		Log(hourly wage)		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, hiring 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. CPS 1979-2008: Cyclicality of unemployment rates, by wage group (Robustness checks)

		Log(hourly wage)		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, hiring 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.