Separations, Sorting and Cyclical Unemployment*

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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. Using micro-data from the Current Population Survey for the years 1962-2012, it documents that in recessions the pool of unemployed shifts towards workers with high wages in their previous job. These shifts are associated with both observed and unobserved factors in the wage and are mainly driven by the high cyclicality of separations of high-wage workers. The paper evaluates a number of theories that can potentially account for this new fact about the composition of the unemployed.

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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 micro data from the Current Population Survey (CPS) for the years 1962-2012, 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, experience, 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.

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 the 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.

The findings also have implications for the measurement of the cyclicality of statistics related to the unemployed. Similar to Solon, Barsky and Parker (1994) who showed that compositional changes among the employed lead to an understating of the true cyclicality of real wages, the findings in this paper suggest that the cyclicality of any statistic related to the unemployed is potentially subject to composition bias. These biases may be substantial, as the compositional changes in the pool of unemployed are shown to be of much larger magnitude than the compositional changes among the employed. Moreover, the findings

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1 See also Ravenna and Walsh (2012) who set up a model with endogenous separations and find that shifts towards low-ability workers in recessions have important implications for monetary policy.

2 Appendix G.1 compares steady state elasticities of the aggregate job finding rate in a search-matching model with exogenous shocks to separation rates. Similar to Pries (2008), a calibration of the model with shifts towards low-ability workers in recessions amplifies the response of the job finding rate by a factor of 2.2, whereas a calibration that matches the patterns of separations documented in this paper implies a dampening of the response of job finding by a factor of up to 3.6.
suggest that it is not sufficient to control for demographic characteristics as the pool of unemployed shifts towards high-residual wage workers in recessions. The compositional changes may affect - among others - the measurement of the cycicality of search intensity, the cyclicality of reservation wages, the cyclicality of wages of newly hired workers, as well as the cyclicality of program effects, such as the effects of unemployment insurance or job training programs.

Given the importance of the new fact that I document in the first part of the paper, the second part of the paper tries to explain it. To this purpose, I set up a search-matching model with endogenous separations, worker heterogeneity in terms of ability and aggregate productivity shocks. The baseline calibration of the model predicts shifts in the pool of unemployed towards low-ability workers in recessions, and thus is inconsistent with the new facts. An alternative calibration of the model, which allows for the variance of match-specific productivity shocks to differ between low- and high-ability workers, produces shifts towards high-ability workers in recessions in line with the documented facts. This calibration, however, is not supported by additional evidence, which shows that the variance of wage changes on a given job is very similar between low- and high-wage workers.

Another explanation for the compositional changes among the unemployed is related to the fact that layoffs in downturns often occur due to death of firms, plants or even smaller units within a firm. To the extent that these shocks affect workers indiscriminately of type, they lead to shifts towards high-ability workers in recessions. The reason is that the pool of unemployed is negatively selected towards low-ability workers and thus indiscriminate separation shocks increase the proportion of high-ability workers among the unemployed. I find that cyclical plant death can account for a substantial part of the compositional shifts towards high-ability workers in recessions.

Finally, an additional and potentially complementary explanation for the findings is related to the fact that firms often face tightening credit constraints in recessions when liquidity dries up in financial markets. To capture this idea, I extend the baseline model by introducing a constraint on cash flows, which produces more cyclical separations for high-ability workers and thus shifts towards high-ability workers in recessions. The intuition for this finding is that - in the absence of constraints - firms are willing to pay workers above cur-

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3 See Appendix J for back-of-the-envelope calculations of the potential magnitude of these biases.
4 E.g., Card, Kluve and Weber (2015) conduct a meta-analysis of active labor market programs and find that they tend to be more effective in recessions. As noted by the authors, this finding may be driven by changing characteristics of program participants in recessions.
5 Baker (1992) and more recently Krueger, Cramer and Cho (2014) and Kroft et al. (2014) find that the cyclicality of unemployment duration and job finding is not affected by composition bias. The main reason for this finding is that job finding rates do not differ much across wage groups and thus even large compositional shifts have a small or no impact on the aggregate job finding rate and unemployment duration.
rent match productivity if they are compensated by positive future cash flows. If firms, however, face a constraint 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 marginal matches with high-ability workers produce more negative cash flows and thus are more sensitive to a credit tightening. Despite this success, the theory cannot account for shifts towards high-wage workers in recessions that do not show any signs of credit tightening and thus is unlikely to be the only explanation for the facts documented in this paper.

1.1 Related Research

The empirical patterns may appear to contradict findings from a related literature on the cyclicity of real wages. Specifically, Solon, Barsky and Parker (1994) documented that the measured cyclicity 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 unweighted wage data, composition bias has almost no effect on the cyclicity 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 consistent with small shifts towards high-wage workers in the pool of employed.

The analysis in this paper also differs in important respects from Bils, Chang and Kim (2012) who study the cyclical patterns of employment, separations and job findings for different wage and hours groups with the Survey of Income and Program Participation (SIPP) for the years 1983-2003. Their main finding is that high-wage/high-hours groups have more cyclical employment, separations and job findings relative to the predictions of a calibrated search-matching model with worker heterogeneity. The main focus of my paper is the composition of the unemployed and how it changes over the business cycles, and thus it analyses direct measures of the composition of the pool of unemployed. This allows assessing not only the direction of the changes in the composition but also their magnitude, which is shown to be substantial and much larger than the compositional changes in the pool of employed. It is important to note that, while with the findings in this paper are consistent with the empirical findings of Bils, Chang and Kim (2012), my facts about the compositional changes in the pool of unemployed are not implied by their findings. In this paper, I derive
equations that show - in an accounting sense - the relationship between the composition of the unemployed, the composition of the employed, the composition of the labor force and the cyclicity of worker flows for different wage groups. These equations reveal that it is important to assess the cyclicity of all group-specific worker flows, to measure these flows in logs and to assess the cyclicity of the composition of the labor force, before making any inferences about the direction and the magnitude of the changes in the composition of the pool of unemployed. Finally, it is worth noting that the empirical analysis in this paper covers a much longer time period, documents in detail the compositional changes both in terms of worker characteristics and residual wages, and analyzes the cyclicity of the composition of the labor force as well as flows from unemployment to out of the labor force.

The remainder of the paper is organized as follows. Section 2 describes the different data sources. Section 3 carries out the empirical analysis. Section 4 sets up the search-matching model with endogenous separations and heterogeneous workers, and reports simulation results for different calibrations of the model and different sources of aggregate shocks. The section also discusses the relevance of alternative theories, such as compensating differentials and wage rigidity, for the facts described in this paper. Section 5 concludes the paper.

2 Data Sources

The main empirical analysis in this paper is based on micro data from the Current Population Survey (CPS). 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 in 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).

In what follows, I describe the three main samples from the CPS that I use for my analysis. The main reason for using data from the CPS is the large sample size, as the main focus of my analysis is the relatively small sub-sample of unemployed. I also use data from the National Longitudinal Survey of Youth 1979 (NLSY79) to extend the main analysis with
longitudinal data on wages and labor force outcomes.

**Matched CPS ORG Sample.** The main focus of the empirical analysis is on 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. This sample merges wage data from the CPS ORG files with data on labor force status from the monthly CPS files. More precisely, I restrict my sample to all individuals with available wage data from the fourth interview and analyze 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. While the data cover the years 1979-2012, there is no information on wages at the prior job that is available for 1979, and thus the sample of unemployed workers in my analysis covers the years 1980-2012.

The CPS does not follow individuals who move out from an address surveyed in a previous month. This gives rise to substantial attrition between the fourth interview when individuals report their wage and the subsequent interviews 9 to 12 months later (as shown by Figure 1, there is a gap of 8 months between the 4th and the 5th interview): 28.9% of the individuals in my sample had no match in interviews 5-8. Similar to Bleakley, Ferris and Fuhrer (1999), I adjust the survey weights to account for attrition based on observable characteristics such as sex, age, education, race and marital status.

Following Lemieux (2006), I restrict my sample to individuals aged 16 to 64 with positive years of potential experience, exclude all observations with allocated earnings except where allocation flags are not available and remove observations with hourly wage values less than $1 or more than $100 in 1979 dollars (see the Appendix A for details). I also restrict my sample to workers in the private sector, who are not self-employed and not self-incorporated, though including them does little to affect the results. The total sample size is 1,203,455 individuals, where each individual has up to three monthly transitions between labor market states (between interviews 5 to 6, 6 to 7 and 7 to 8). Out of these 1,203,455 individuals, 79,450 experienced at least one month of unemployment in interview months 5-8.

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6 The main concern 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 (2013).

7 See Appendix A for details. Abowd and Zellner (1985) propose a reweighing procedure that minimizes the difference between the stocks implied by the worker flow data and the official CPS stocks. This procedure is not available here because the CPS does not report the stocks of unemployed by wage on the previous job.

8 See Appendix Tables C.1 - C.4.

9 Table A.1 in the Appendix provides a comparison of the different data sources in terms of demographic characteristics. The demographics in the monthly CPS files should be fully representative of the U.S. population aged 16 to 64, whereas the matched CPS ORG and the March CPS sample impose restrictions in terms of employment in the prior calendar year, which increases the proportion of workers with characteristics associated with higher employment rates. The NLSY79 is a representative cohort of workers and thus not
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. Notice, however, that the median reported duration of unemployment was less than three months for the period prior to the recent recession according to official statistics of the Bureau of Labor Statistics (BLS), and the fraction of those with unemployment durations above one year averaged only 8.8% and never exceeded 13.3% for the years 1979 to 2008, which suggests that the constraint imposed by the sample-selection criterion is relatively minor. More recently, the share who indicated that they have been unemployed for more than 12 months increased dramatically to as much as 31.2% in 2011, and, thus, the results with respect to the later period have to be taken with some caution. It is important to note, however, that the data on self-reported duration is inconsistent with the data on transitions from unemployment to employment in the more recent data (see Elsby et al., 2011, and Rothstein, 2011). Based on my estimates, only around 11% of unemployed workers had unemployment durations longer than 12 months in this period. The sample also does not include those who were classified as out of the labor force at the time of their 4th CPS interview, which is why I turn to additional data from the monthly CPS files.

**Monthly CPS.** I use all data from the basic monthly CPS surveys for the years 1978 to 2012. While the monthly CPS files do not have information on wages, they allow for a comparison of the results from the analysis with the matched CPS ORG sample based on demographic characteristics. These data are fully representative of the sub-population of unemployed workers, as they are not restricted to individuals who were employed a year ago and thus include the long-term unemployed as well as those who enter unemployment from out of the labor force. Therefore, I can directly test whether, in terms of observable characteristics, the sample restrictions in the CPS ORG data lead to biases in the analysis of the composition of the unemployed. An additional advantage is the large sample size, for information from all eight interviews can be used for the analysis. The total sample size is 35,052,936 observations out of which 1,656,494 were unemployed at the time of the survey.

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10These numbers are taken from the OECD’s statistics of "Incidence of unemployment by duration".
11The monthly U-to-E transitions rate in the CPS data was stable over the years 2009-2012 at around 17%.
12In steady state, the fraction of unemployed with duration longer than 12 months is \( \prod_{d=1}^{12} (1-f_d) \), where \( f_d \) is the job finding probability at month \( d \) of the unemployment spell. For the purposes of the calculation reported in the text, I assumed that the probability of finding a job is constant over the spell of unemployment.
13In some cases, I restrict the sample to the years 1980-2012, to be comparable to the CPS ORG sample.
March CPS. I also extend the analysis with the merged CPS ORG sample with data from the CPS March supplement, which is available since 1962. Besides the extended sample period, an additional advantage of the March supplement is that it does not rely on matching individuals across different interviews, since data on wages in the previous year are available from the same interview. Thus, it provides a direct test of whether differential attrition by wage group is biasing my results in the analysis with the CPS ORG sample. A further advantage is that the sample restriction of available wage data in the past calendar year requires a weaker labor force attachment compared to the CPS ORG files, as it includes any person that had worked at any point (for at least one week) in the past calendar year and includes individuals who have been unemployed for up to 14.5 months compared to 12 months for the monthly data (the interview date is in the middle of March). The CPS March supplement, however, is only available once per year and thus does not allow for the analysis of worker flows. I use the same sample restrictions as in the analysis with the CPS ORG and monthly data and follow Lemieux (2006) and Autor, Katz and Kearney (2008) in the construction of the sample (see Appendix A for details). The sample size is 2,637,433 out of which 140,311 were unemployed at the time of the March interview.

NLSY79. I use data from the NLSY79 for the years 1979-2010, which is a nationally representative longitudinal survey of young men and women who were between the ages of 14-22 when they were first interviewed in 1979. These individuals were interviewed on an annual basis in the years from 1979 to 1993, and on a bi-annual basis for the period 1994-2010. The main focus in the analysis with the NLSY79 is the distinction between permanent and transitory components of the wage and, thus, I restrict my sample to individuals with at least 10 years of valid wage data. Beyond that, I use the same sample restrictions and apply the same treatment of outliers of wage observations as in the CPS data. The sample size is 6,818 individuals and 129,809 interviews. In 26,263 interviews respondents indicated that they were unemployed over the course of the past year for at least one week.

3 Empirical Analysis

The main focus of this paper is to analyze the compositional changes in the pool of unemployed over the business cycle. It is well known that the cyclical volatility of unemployment is higher for low-skilled and younger workers. Moreover, Solon, Barsky and Parker (1994)

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13 This restriction refers to having worked at least one week in the past year (and not being employed at the time of the survey). Thus, it requires only minimal labor force attachment during the past year.

14 To increase the sample size, the pool of unemployed is defined as those unemployed at some point in the past calendar year weighted by their duration of unemployment (see the Appendix A for details).
showed that the pool of employed shifts toward high-wage workers in recessions. One may conclude from these facts that the composition of the pool of unemployed shifts towards low-skilled workers in recessions (see, e.g., Pries, 2008). However, as shown below, these facts do not necessarily imply shifts among the unemployed towards low-skilled workers in recessions, and may be fully consistent with compositional changes towards high-skilled workers. In what follows, I first derive equations that show the relationship between the composition of the unemployed, the composition of the employed, the composition of the labor force and the cyclicality of group-specific worker flows, and then turn to the empirical analysis of the cyclicality of the composition of the pool of unemployed.

3.1 Measurement

The fraction of unemployed from group $i$ at time $t$, $\phi_{it}^U$, can be written as:

$$\phi_{it}^U = \phi_{it}^L \frac{U_{it}}{U_t},$$

(1)

where $U_{it}$ is the unemployment rate of group $i$, $U_t$ is the aggregate unemployment rate, and $\phi_{it}^L$ is the fraction of group $i$ in the labor force. Changes in the share $\phi_{it}^U$ thus can be attributed to changes in the proportion of the group-specific unemployment rate relative to the aggregate unemployment rate, as well as to movements in the composition of the labor force. Therefore, the higher volatility of the unemployment rate of low-skilled workers does not warrant the conclusion that the pool of unemployed sorts towards low-skilled workers in recessions. The reason is that low-skilled workers also have a higher average unemployment rate and thus changes in the ratio shown in equation (1) may increase or decrease in downturns.

The Relationship to the Composition of the Employed. A transformation of equation (1) above gives the cyclicality of the share of group $i$ among the unemployed:

$$\frac{d \ln \phi_{it}^U}{d \ln U_t} = \frac{d \ln U_{it}}{d \ln U_t} - 1 + \frac{d \ln \phi_{it}^L}{d \ln U_t}.$$  

(2)

One can approximate the cyclicality of the share of group $i$ among the employed as follows$^{15}$:

$$\frac{d \ln \phi_{it}^E}{d \ln U_t} \approx -\frac{U_t}{1 - U_t} \left[ \frac{\phi_{it}^U}{\phi_{it}^E} \frac{d \ln U_{it}}{d \ln U_t} - 1 \right] + \frac{d \ln \phi_{it}^L}{d \ln U_t}.$$  

(3)

$^{15}$Log changes for variable $x_{it}$ are defined as $d \ln x_{it} = \ln x_{it+1} - \ln x_t$. Equation (3) is based on a linear approximation. See Appendix B for details.
Comparing equations (2) and (3), it is easy to see that if $\phi_{it}^U$ is equal to $\phi_{it}^E$ and if there are no changes in the composition of the labor force, then the composition of the pool of employed moves in the opposite direction of the composition of the pool of unemployed. However, if $\phi_{it}^U$ is sufficiently different from $\phi_{it}^E$ or if the composition of the labor force changes, then the two pools may shift in the same direction. Intuitively, if the quality of the pool of unemployed is skewed towards low-skilled workers, then an individual that is below average among the employed may be above average among the unemployed and thus moving this individual from the employed to the unemployed improves the quality of both pools. To conclude, one cannot directly infer the compositional changes in the pool of unemployed from compositional changes in the pool of employed and vice versa, as differences in the average quality of the pools and movements in the composition of the labor force play a potentially important role in the relationship between the composition of these two pools.

The Importance of the Ins and Outs for the Composition of the Unemployed. 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

\[ dU_t \approx U_t^{ss}(1 - U_t^{ss}) [d\ln s_t - d\ln f_t], \quad (4) \]

where $U_t^{ss} = \frac{s_t}{s_t + f_t}$ is the flow steady state unemployment rate. Given equations (4) and (2), and assuming constant labor force participation, it can be shown that changes in the share of group $i$ in the pool of unemployed can be decomposed into

\[ d\ln \phi_{it}^U \approx (1 - U_t^{ss}) [d\ln s_{it} - d\ln f_{it}] - (1 - U_t^{ss}) [d\ln s_t - d\ln f_t], \quad (5) \]

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 changes in the log of the aggregate separation and job finding rate. Given that $(1 - U_t^{ss})$ is very similar across groups, one can directly conclude from the magnitude of the changes in the group-specific log separation and job finding rates which margins are more important for the changes in the composition of the pool of unemployed. Note that it is important for the purposes of this decomposition to take the log of these flow rates, as average separation rates are shown to differ substantially across groups and thus, the cyclicality of the separation rate (not in logs) is less informative about the compositional changes in the pool of unemployed.
3.2 The Cyclicality of the Composition of the Unemployed

I start by providing direct evidence on the composition of the unemployed in terms of demographic characteristics from the monthly CPS files. Figure 2 shows the ratios of the group-specific unemployment and employment rates relative to a baseline group for the period 1978-2012. As demonstrated above, changes in the ratios give direct evidence of changes in the composition of the pool of unemployed. It is apparent from the graph that the ratio of unemployment rates of those of age 20-29 to those of age 40-49 is strongly negatively correlated with the yearly HP-filtered unemployment rate,\(^\text{16}\) as is the ratio of unemployment rates of those with less than a high school degree to those with a high school degree. Strong positive correlations are visible for the ratio of unemployment rates of those married to those not married, male to female and to a lesser extent for those with some college education to those with a high school degree (at least for the period after 1990). Interestingly, for those groups typically associated with lower wages the correlation is negative, whereas for those groups typically earning higher wages compared to the base group the correlation tends to be positive, though the magnitude of these correlations differs across groups. Figure 2 also shows the cyclicality of the ratios of employment rates, which appear acyclical in the figure. However, the picture is somewhat misleading as in general the ratios of employment rates change in the same direction as the ratios of unemployment rates but on a much smaller scale, see the Appendix Table B.1 for details. The same table also shows the movements in the ratios of labor force participation rates, which tend to go in the same direction as the ratios of unemployment rates but the cyclicality is usually up to an order of magnitude smaller, suggesting that changes in the composition of the unemployed is driven only to a small extent by changes in the composition of the labor force (to see this, compare the first and second term in equation 2).\(^\text{17}\) Overall, this evidence suggests that the pool of unemployed sorts towards individuals which are usually associated with higher wages, and for most demographic characteristics, the pool of unemployed sorts in the same direction as the pool of employed, but much more strongly so.

To evaluate more systematically, the extent to which the composition of the pool of unemployed sorts towards high-wage groups in downturns, I turn to the matched CPS ORG sample and the March CPS sample, where I have information on hourly wages from the previous year. I use the wage on the previous job (from the previous year) as a summary

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\(^{16}\) Note, however, that I did not find any strong correlations for the ratios of unemployment rates for those age 30-39 or those of age 50-59 to those of age 40-49 (see Appendix Table B.1 for details).

\(^{17}\) However, this does not necessarily imply that the labor force participation margin is irrelevant for compositional changes in the pool of unemployed, due to a potential stock-flow fallacy, as highlighted in a recent paper by Elsby, Hobijn and Sahin (2013) who analyze the importance of labor force participation for aggregate fluctuations in unemployment.
Figure 2: Ratios of group-specific unemployment and employment rates for the years 1978-2012

Note: All series are yearly averages, HP-filtered with smoothing parameter 100.
indicator of compositional changes in the pool of unemployed. Panel (a) in Figure 3 plots the
average wage from the previous year by current labor force status. More precisely, it shows
the average wage for those who were employed in interview 4 but unemployed in interview
8 of the CPS, as well as the average wage of those who remained employed. Note that the
left-hand side shows the magnitude for the natural logarithm of the previous wage, whereas
the axis on the right-hand shows the magnitude for the unemployment rate, and both series
are yearly and hp-filtered with smoothing parameter 100. 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 0.60). Moreover, the magnitude of the
compositional changes is considerable, as the average change from trough to peak is more
than 10 log points (i.e., more than 10 percent). Panel (a) in Figure 4 shows very similar
patterns for the cyclicality of the average wage from the previous year, using the data from the
March CPS over the period 1962-2012 (the correlation coefficient is 0.56). The table further
shows that the patterns appear in every single recession since 1962, and the magnitude of
the changes is very similar across the two data sources.

One way to assess the magnitude of the compositional shifts is to compare them to typical
movements in the aggregate labor productivity. Shimer (2005) finds that over the post-war
era, the standard deviation of the aggregate labor productivity in the U.S. was 2 log points.
A one-standard deviation increase in the detrended aggregate unemployment rate predicts a
shift in the composition of the pool of unemployed of 2.75 log points in terms of the previous
wage. Therefore, if one interprets the compositional shifts in terms of the previous wage
as purely reflecting changes in the potential productivity of the unemployed, these shifts
are larger than (and in the opposite direction of) the typical movements of aggregate labor
productivity over the U.S. business cycle.

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,
if 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 pat-
terns in Panel (a) of Figures 3 and 4, then the average wage rank should show no correlation
with the aggregate unemployment rate. However, Panel (b) in the same figures shows a very
strong correlation of the average wage rank of the unemployed with the aggregate unem-

\footnote{The unemployment rate is taken from the official tables of the Bureau of Labor Statistics.}

\footnote{One might also note that the compositional changes seem to be slightly leading the unemployment rate.
The reason is that - as documented further below - the changes in the pool are driven by the differential
cyclicality in job separations, which tend to lead the unemployment rate.}
Figure 3: The average wage from the previous year by employment status in the matched CPS ORG sample (1980-2012).

Note: All series are yearly averages, HP-filtered with smoothing parameter 100.
Figure 4: The average wage from previous year by employment status in the CPS march supplement (1962-2012).

(a) Raw wage

(b) Wage rank

(c) Mincer-residual

Note: All series are yearly averages, HP-filtered with smoothing parameter 100.
ployment rate. The correlation coefficient is 0.68 (March CPS: 0.71), suggesting that wage compression plays no role. In terms of the magnitude, a percentage-point increase in the unemployment rate is, on average, associated with a 1.4 percentage-point increase (March CPS: 1.1 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.

Panel (c) in Figures 3 and 4 shows the same plot but for the residual of a Mincer-style regression of the log wage on observable characteristics such as potential experience, educational attainment, gender, marital status, 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 in the previous year, with a correlation with the unemployment rate of 0.45 (March CPS: 0.60). The magnitude is smaller as a percentage-point increase in the unemployment rate leads to a 0.75% increase (March CPS: 0.95%) in the average residual wage of the unemployed, as compared to a 2.74% increase (March CPS: 2.59%) in the average raw wage in Panel (a). This suggests that both observed and unobserved factors contribute to the compositional changes in the unemployment pool over the business cycle.

To get a better sense of what observable factors drive the compositional changes in the unemployment pool, I regress the detrended series of each component of the predicted wage for those currently unemployed on the detrended aggregate unemployment rate. The results in Table 1 show that, compared to periods of low unemployment, the unemployed in recessions are more experienced, more educated, more likely to be male, more likely to be married, more likely to be white, and more likely to come from industries and occupations that pay high wages. Some of these patterns might be well-known, such as the cyclical changes in the composition of unemployed by gender or industry, but it is striking that all observable components contribute to the changes in the pool of unemployed in the same direction. In terms of the magnitude, the predicted wage from industry dummies contributes about one quarter to the total of the compositional changes, whereas the predicted wage of other demographic determinants of the wage and the residual contribute the remaining three fourths. The results are surprisingly similar between the estimates from the matched CPS ORG sample and the March CPS sample. This demonstrates that attrition is not causing any major bias in my estimates with the matched CPS ORG sample, as the March CPS contains backward looking information on wages in the previous year and thus does not rely on matching individuals across survey waves.

One drawback of the analysis with the data from the matched CPS ORG sample is that

---

20 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.

21 See the footnote in Table 1 below for details.
it restricts the sample to those who were employed twelve months ago and thus excludes the very long-term unemployed, those who exited the labor force and re-enter after a prolonged period of joblessness as well as those who newly enter the labor force. A similar issue affects the analysis with the CPS March supplement as it restricts the analysis to those who had a minimal work history in the prior year. For this reason, I checked the robustness of my findings by analyzing the predicted wage for the sample of unemployed in the monthly CPS, which is fully representative of the subpopulation of unemployed workers. Row 3 of Table 1 shows the predicted wage for the sample of unemployed in the monthly CPS files (the predicted wage is computed from the same regression coefficient as for the predicted wage in row 1 of the same Table). In contrast to the sample used for row 1, this sample includes the long-term unemployed and those who were out of the labor force for longer than 12 months. Moreover, it does not face issues related to attrition and has a much large sample size as it uses data from all eight interviews of the CPS.\textsuperscript{22} The results show that the compositional changes in the pool of unemployed are very similar for both samples, at least in terms of the predicted wage, which suggests that excluding the long-term unemployed and those entering unemployment from out of the labor force does little to affect the magnitude of the compositional changes of the unemployed over the business cycle.

Note that throughout the paper I use the detrended aggregate unemployment rate as a cyclical indicator, but the main results are very similar when I instrument the detrended aggregate unemployment rate with detrended real GDP and use the predicted value as a cyclical indicator (see the results in Appendix Table C.1).\textsuperscript{23} Another 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 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 recessions.\textsuperscript{24}

\textsuperscript{22}The results in Table 1 are robust to using data from rotation group 2 only, which suffers from the least attrition. Similarly, the results in Appendix Table B.1 are not sensitive to restricting the sample to rotation group 2 only. This suggests that my results on the compositional changes of the pool of unemployed are not driven by rotation group bias.

\textsuperscript{23}The Appendix Table C.1 contains further robustness checks with the CPS ORG sample, showing that results in terms of the previous wage, the wage rank and the wage residual are very similar if one restricts the sample to different subsamples (men only, age 25-54, with some college education or more, full-time workers, or not in manufacturing/construction) or includes public sector employees. The table also shows that the results are quantitatively similar if one restricts the sample to job losers or to those on layoff. This suggests that the compositional changes in the pool of unemployed are mainly driven by changes within types of unemployed rather than changes in the relative shares of job losers and job leavers. Finally, the results are robust to different filtering of the data and different assumptions in the construction of the wage variable.

\textsuperscript{24}See also Figure 3 in the Appendix C, which shows the distribution of unemployed workers by wage decile in times of high and low unemployment.
A potential limitation of the analysis of compositional changes in terms of the previous (residual) wage may be that it not only reflects changes in worker characteristics but also changes in the characteristics of the employers where the workers worked in the previous year. In particular, it is well documented that larger employers pay higher wages, even when controlling for demographic characteristics, occupation and industry (see Brown and Medoff, 1989, and the related literature). Fortunately, from 1989 onwards, the March CPS does have information on the size of the employer for the longest job held in the prior year. Therefore, I can examine to what extent controlling for employer size affects the compositional changes in the pool of unemployed in terms of the residual wage. To this purpose, I estimate the same wage regression as for the baseline results reported in Table 1 but for the period 1989-2012 and include four dummies for employer size (0-99, 100-499, 500-999, 1000+) relative to employer size 0-99.  

\[ w_t = a + \beta \text{Employer Size}_t + \epsilon_t \]

As expected, employer size has a powerful effect on the hourly wage, with an effect of .10, .14, and .18 resp. for the dummies of employer size 100-499, 500-999, and 1000+ resp. relative to employer size 0-99.

This may seem in contradiction with Moscarini and Postel-Vinay (2012) who document in great detail that large employers on net are more cyclically sensitive in terms of employment growth compared to small employers. However, it is possible that the differential net employment growth patterns documented by Moscarini and Postel-Vinay are driven by differential hiring rates rather than separation rates across large

### Notes
Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; (i) The years 1962-67 were not included as no information was available on industry in previous year. All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cyclicality is measured as the coefficient $\beta$ in the regression $\log(w_{t-1}) - \log(w_t) = \alpha + \beta U_t + \epsilon_t$, where $w_t$ is the average wage from the previous year for those unemployed at time $t$, $w_{t-1}$ is the average wage from the previous year for the full sample, and $U_t$ is the official unemployment rate from the Bureau of Labor Statistic. Note that the coefficients on the predicted and residual wage add up to the coefficient on the raw wage. Source: The author's estimates with data from the merged CPS Outgoing Rotation Group sample for the years 1980 to 2012, the monthly CPS files for the years 1980 to 2012, the CPS march supplement for the years 1968 to 2012, and the NLSY79 for the years 1979 to 2010.
Table 1 provides evidence on the compositional changes in the pool of unemployed in the NLSY79, which has up to 24 years of data for each individual. Despite the differences in sample design, the main results from the CPS replicate in the NLSY79 data both in terms of the raw and the residual wage. Moreover, the magnitude of the estimates is similar to the magnitude of the estimates in the CPS data. The main advantage of the NLSY79 is that it is possible to decompose the compositional changes in terms of the residual wage in a persistent component and a purely transitory effect. To do so, I use the residual from the wage regression, run a second-stage regression of this residual on individual fixed effects, and then compute the average fixed effects and average residual (the transitory effect) from this second-stage regression among the unemployed each year. The results show that the compositional changes in terms of the residual wage are mainly driven by the individual fixed effect and very little is explained by the transitory effect, suggesting that the pool of unemployed sorts towards workers with high unobserved ability in recessions. Of course, the individual fixed effect measures the average residual wage over the period of observation, and thus it is possible that the fixed effects capture in part job- or employer wage-effects for individuals with little job turnover. However, if this holds true, then as long as individuals change jobs at least once over the sample period (which nearly all individuals in the sample do), one would expect compositional changes in the pool of unemployed in terms of the transitory effect. Moreover, as shown in the Appendix Table C.7, the results are very similar when I include in the sample only individuals who changed jobs 5 times or more over the sample period. Overall, the estimates in the NLY79 provide evidence that the compositional effects in terms of the residual wage are not driven by transitory effects.

If the results are driven by differential hiring rates across large and small employers, then we would not expect to see any changes in the composition in the pool of unemployed in terms of the size of the employer of the previous job, as it would only affect the size of the new employer. More recently, Moscarini and Postel-Vinay (2014) document gross flows for the great recession and find that “hire rates collapsed at the larger establishments and not at the smaller ones” (p. 7), consistent with this hypothesis. The coefficient on the raw wage is somewhat lower than in the CPS data, but this is to be expected, given that the NLSY79 follows a cohort of individuals with little differences in age and, to some extent, also less variation in educational attainment than in the full population. This is reflected in the coefficient estimates for the cyclicality of the pool in terms of experience and educational attainment, which are both insignificant. As for the remaining characteristics, the results are broadly in line with the CPS estimates.

It is possible to estimate individual fixed effects directly in the first-stage wage regression, but this would include observed and unobserved fixed characteristics such as gender or race, as these variables are collinear to the individual fixed effect and thus would drop out from the regression. If job- and employer effects are important, one would also expect the results to depend on the length of the panel, as these effects should average out in longer panels. The results reported in Appendix Table C.7 show little change when we include in the sample only individuals with 15 years of valid wage data or more (or 5 years of valid wage data or more). These results are also in line with work in progress with Peter Fredriksson (Stockholm University) and Björn Öckert (Uppsala University), where we match unemployment register data to data on cognitive and non-cognitive test scores from military enlistment for the years 1991 to 2011. We construct a skill index by
3.3 The Cyclicality of the Ins and Outs 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 unemployment and/or the different behavior of outflows from unemployment across wage groups. To analyze this in detail, I look at the worker flow data from the CPS ORG sample to determine whether the patterns documented in the previous section are due to job separations or job findings. In particular, I divide the sample in each year into those below and above the median wage and analyze 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 below or above the median wage in interview 4 each year, and the transitions are analyzed for subsequent interviews (i.e., monthly transitions between interviews 5, 6, 7 and 8).

As shown in equation (5), one can directly conclude from the magnitude of the changes in the group-specific log separation and job finding rates which margins are more important for the changes in the composition of the pool of unemployed. For this reason, I run the following regressions:

\[
\ln x_{it} = \alpha^x_i + \beta^x_i \ln U_t + \varepsilon^x_{it},
\]

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 percent increase in \(x_{it}\) in response to a 1% increase in the aggregate unemployment rate (the coefficient \(\beta^x_i\)). All series are monthly, seasonally adjusted, and detrended with an HP-filter with smoothing parameter 900,000.\(^{31}\)

Table 2 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 on average lower for high-wage workers than for low-wage workers. The main new result, however, is that the cyclicality of separations is almost twice as large for individuals with high wages compared to those below the median.\(^{32}\) The relating these cognitive and non-cognitive test scores to wage data, and find that the average skill of the unemployed increases in recessions, and that this increase is mostly driven by non-cognitive skills.

\(^{31}\)I follow Bils, Chang and Kim (2009) who detrend the monthly time series with an HP-filter with smoothing parameter 900,000. This is the equivalent of Shimer’s (2005) detrending choice of a smoothing parameter of 100,000 for a quarterly time series. The published version of Bils, Chang and Kim (2012) does no longer follow this detrending choice. Appendix Tables C.2, C.3 and C.4 show that my results are robust to HP-filtering with a smoothing parameter of 14,400.

\(^{32}\)My results are also consistent with Fujita and Ramey’s (2009) analysis who show that - using CPS worker flow data from 1976 to 2005 - that separations account for approximately 50% of the overall volatility.
**TABLE 2. THE CYCLICALITY OF SEPARATION, JOB FINDING AND UNEMPLOYMENT RATES, BY WAGE GROUP (BELOW AND ABOVE MEDIAN)**

<table>
<thead>
<tr>
<th></th>
<th>A. Based on hourly wage</th>
<th>B. Based on Mincer residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td><strong>Separation rates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.014</td>
<td>0.007</td>
</tr>
<tr>
<td><strong>Cyclicality</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(s.e.)</td>
<td>(0.08)*****</td>
<td>(0.09)*****</td>
</tr>
<tr>
<td><strong>Job finding rates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.32</td>
<td>0.31</td>
</tr>
<tr>
<td><strong>Cyclicality</strong></td>
<td>-0.55</td>
<td>-0.66</td>
</tr>
<tr>
<td>(s.e.)</td>
<td>(0.05)*****</td>
<td>(0.08)*****</td>
</tr>
<tr>
<td><strong>Unemployment rates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.045</td>
<td>0.024</td>
</tr>
<tr>
<td><strong>Cyclicality</strong></td>
<td>0.78</td>
<td>1.39</td>
</tr>
<tr>
<td>(s.e.)</td>
<td>(0.02)*****</td>
<td>(0.04)*****</td>
</tr>
</tbody>
</table>

*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 cyclicality is measured as the coefficient $\beta$ in the regression $\ln(x_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where $x_{it}$ is the separation, job finding or unemployment rate of group $i$ at time $t$ and $U_t$ is the sample unemployment rate. I instrument the sample unemployment rate with the official unemployment rate because of possible attenuation bias due to measurement error. Sample size: 370 monthly observations. Source: The author’s estimates with data from the matched CPS ORG sample for the years 1980 to 2012. As described in the main text, this sample includes data from the monthly CPS files for the interviews 5, 6, 7 and 8, matched to the wage record in interview 4 from the CPS ORG files.

The difference is somewhat smaller when looking at the cyclicality of separations for those below and above the median residual wage: The ratio of $\frac{\zeta_{\text{sep}}}{\text{low}}{\zeta_{\text{sep}}}{\text{high}}$ is 0.68 compared to 0.43 for the cyclicality with the raw wage measure. These results are also consistent with the findings in Bils, Chang and Kim (2012) who split their sample from the SIPP into four groups - by low or high hours and by low or high wages - and report the cyclicality of separations, hirings, employment and hours worked. Averaging the cyclicality of separations across the hours groups, one finds that the ratio of the cyclicality of separations between the low- and high-wage group is 0.54, which is similar to my results in the CPS data.

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.

of unemployment. Using Elsby, Michaels and Solon’s decomposition in equation 4, separations account for 38% of the volatility of unemployment for the low-wage group and for 55% for the high-wage group.
These facts are robust across a large range of different specifications and sample selection criteria (see Appendix Tables C.2, C.3 and C.4). Finally, I use Fujita and Ramey’s (2009) adjustment for time aggregation bias and find that the differences in the cyclicity of separations are even stronger for those below and above the median wage (see Appendix Tables C.2 and C.3). Appendix Table C.5 also shows the baseline results but splitting the quartiles of the wage distribution each year instead of below and above the median. The results are very similar and show that separations are most cyclical in the top quartile of the distribution of the hourly wages, suggesting that the proportion of unemployed workers coming from the top quartile increases in times of high unemployment.\footnote{33See also Figure 3 in the Appendix, which shows the distribution of unemployed by decile of the distribution of wages from one year ago, for times of both high and low unemployment.}

How do the compositional changes among the unemployed relate to compositional changes among the employed? One can put the estimates of Panel A of Table 2 into equations (2) and (3) above, which gives $\frac{d \ln \phi_{U_{high}, t}}{d \ln U_t} = 0.39$ and $\frac{d \ln \phi_{E_{high}, t}}{d \ln U_t} = 0.002$.\footnote{Note that I used the fact that $\frac{\phi_{U_{high}, t}}{\phi_{E_{high}, t}} = \frac{U_{high, t}}{E_{high, t}} \frac{1-U_t}{1-U_{high, t}}$, and the results from Panel A in Table 2 that $U_t = 0.035$, $U_{high, t} = 0.024$ and $\frac{d \ln \phi_{U_{high}, t}}{d \ln U_t} = 1.39$. For the purposes of this calculation, I abstracted from changes in the composition of the labor force because the CPS data does not have wage information for most of the individuals out of the labor force. Appendix Table B.1 shows that, in terms of observable characteristics, compositional changes in the labor force are an order of magnitude smaller than the compositional changes among the unemployed.\footnote{34See Appendix B.1 for further evidence on the compositional changes among the employed.}} This suggests that the large shifts towards high-wage workers among the unemployed are consistent with very small shifts towards high-wage workers among the employed. Note, however, that the estimates in Table 2 are conditional on being employed in the previous year. To the extent that the composition of the pool of employed in the previous year moves in the same direction, one would expect the movements in the pool of employed to be somewhat stronger. To address this, I computed the cyclicity of the predicted wage for the employed with the Monthly CPS files for the period of 1980 to 2012 and found a coefficient of 0.14 compared to a coefficient of 1.83 for the predicted wage of the unemployed (see row 3 in Table 1). This confirms that the composition of both pools moves in the same direction, but the compositional shifts in terms of the predicted wage are an order of magnitude larger for the unemployed.\footnote{35See Appendix B.1 for further evidence on the compositional changes among the employed.}

### Job-to-Job Transitions and Discouragement

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), and thus one possible explanation for the patterns documented above could be that during good times high-wage workers transition directly from job to job, but during bad times they have to go through a spell of unemployment to find new employment. The original CPS did not ask...
TABLE 3. THE CYCLICALITY OF JOB-TO-JOB TRANSITIONS AND MOVEMENTS FROM UNEMPLOYMENT (U) TO OUT OF THE LABOR FORCE (OLF), BY WAGE GROUP

<table>
<thead>
<tr>
<th></th>
<th>A. Based on hourly wage</th>
<th></th>
<th>B. Based on Mincer residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Job-to-job transitions</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.028</td>
<td>0.018</td>
<td>0.024</td>
</tr>
<tr>
<td>Cyclicality (1994-2012 only)</td>
<td>-0.40</td>
<td>-0.20</td>
<td>-0.32</td>
</tr>
<tr>
<td>(s.e.)</td>
<td>(0.06)*****</td>
<td>(0.06)*****</td>
<td>(0.07)*****</td>
</tr>
<tr>
<td>Transitions from U to OLF</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.150</td>
<td>0.074</td>
<td>0.128</td>
</tr>
<tr>
<td>Cyclicality</td>
<td>-0.37</td>
<td>-0.43</td>
<td>-0.46</td>
</tr>
<tr>
<td>(s.e.)</td>
<td>(0.07)*****</td>
<td>(0.17)*****</td>
<td>(0.08)*****</td>
</tr>
</tbody>
</table>

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. See notes in Table 2 for further details. Source: The author’s estimates with the matched CPS ORG sample for the years 1980 to 2012.

respondents about job switches, but fortunately with the redesign of the CPS in 1994, it became possible to identify those who switched jobs between two monthly interviews (see Fallick and Fleischman, 2004). Table 3 shows the average and the cyclicality of job-to-job transitions for the same groups as in Table 2. 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. This evidence does not support the view that the high cyclical 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 separations into unemployment to be more cyclical for the low-wage group. In other words, the patterns of on-the-job search by high-wage individuals are unlikely to explain the cyclical patterns in the pool of unemployed.

Another possible explanation of the shifts in the pool of unemployed workers towards high-wage workers could be related to worker discouragement. If low-wage workers get discouraged faster in recessions and leave the pool of unemployed towards out of the labor force, then the pool of unemployed should shift towards high-wage workers. Table 3 shows the average as well as the cyclicality of transitions from unemployed (U) to out of the labor force (OLF). On average, low-wage workers tend to leave unemployment more frequently towards OLF. However, the cyclicality between the two groups is almost identical, which suggests that transitions between U and OLF cannot account for compositional changes in the pool of unemployed documented above.

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

In this 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. To this purpose, I set up a search-matching model\textsuperscript{36} with endogenous separations and worker heterogeneity in terms of productivity and evaluate the ability of the model and various extensions of the model to replicate the documented facts.

4.1 A Search-Matching Model with Worker Heterogeneity

There are two types of workers (indexed by $i$) who differ in their market productivity $a_i$ and potentially other parameters. As Bils, Chang and Kim (2012), I assume that firms can direct their search to a particular worker type and thus labor markets are completely segmented.\textsuperscript{37} More precisely, there is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function:

$$M_i = \kappa u_i^\eta v_i^{1-\eta}. \quad (7)$$

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 of the model. I assume that all matches start at the median match productivity $\bar{x}$.

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

$$U_i(Z) = b_i + \beta E[(1 - f(\theta_i))U_i(Z') + f(\theta_i)W_i(Z', \bar{x})|Z], \quad (8)$$

where $Z = [z, \lambda]$ is the aggregate state, $z$ is aggregate productivity and $\lambda$ is an indiscriminate separation shock.\textsuperscript{38} The value of being unemployed depends on the flow-value of unemployment $b_i$ and the discounted value of remaining unemployed or having a job with the value

\textsuperscript{36}The main reference is Pissarides (2000). I deviate from his model by allowing match-specific productivity shocks to be correlated across time.

\textsuperscript{37}The Appendix G.2 discusses a model where search by the firm is non-directed and thus labor markets are not segmented across types. The results of the model with non-segmented labor markets are similar to those of the model with directed search and, if anything, tend to reinforce the conclusions in this paper.

\textsuperscript{38}Equations (8) and (10) implicitly assume that the value of the new match is greater than the value of the outside option, but note that this holds in all aggregate states for all calibrations considered in this paper.
$W_i(Z', \bar{x})$ in the next period. The value function of an employed worker of type $i$ is:

$$W_i(Z, x) = w_i(Z, x) + \beta E \left[ (1 - \lambda) \max \{W_i(Z', x'), U_i(Z') \} + \lambda U_i(Z') \right] Z, x, \quad (9)$$

where $w_i(Z, x)$ is the wage. Whenever the value of the job $W_i$ is lower than the value of being unemployed $U_i$, the worker will separate and thus receive the value $U_i$ in the next period.

The value of posting a vacancy for a firm of type $i$ is:

$$V_i(Z) = -c_i + \beta E \left[ (1 - q(\theta_i))V_i(Z') + q(\theta_i)J_i(Z', \bar{x}) \right] Z, \quad (10)$$

which depends on the vacancy posting cost $c_i$ and the discounted future expected value. The value of a filled vacancy for the firm of type $i$ is:

$$J_i(Z, x) = zxa_i - w_i(Z, x) + \beta E \left[ (1 - \lambda) \max \{J_i(Z', x'), V_i(Z') \} + \lambda V_i(Z') \right] Z, x. \quad (11)$$

Whenever the value of the filled vacancy $J_i$ is lower than the value of the vacancy $V_i$, the firm will fire the worker and thus receive the value $V_i$ in the next period.

Wages are assumed to satisfy the standard Nash-bargaining solution:

$$w_i(Z, x) = \arg \max \left[ (W_i(Z, x) - U_i(Z))^\alpha (J_i(Z, x) - V_i(Z))^{1-\alpha} \right], \quad (12)$$

where $\alpha$ is the bargaining share of the worker, and separations occur whenever the joint match surplus ($S_i(Z, x) = W_i(Z, x) - U_i(Z) + J_i(Z, x) - V_i(Z)$) is negative. Therefore, the reservation match productivity, i.e. the level of match-specific productivity $x$ below which workers and firms decide to dissolve the match, satisfies the efficient-separation condition

$$S_i(Z, R_i(Z)) = 0. \quad (13)$$

Separations are always in the interest of both parties and never unilateral (thus efficient).

**Definition 1** A directed-search equilibrium with Nash-bargaining is defined as the reservation match productivities $R_i(Z)$, the wage schedules $w_i(Z, x)$, the labor market tightnesses $\theta_i(Z)$, and the value functions $U_i(Z)$, $W_i(Z, x)$, $V_i(Z)$ and $J_i(Z, x)$, that satisfy, for each worker type $i$, the Nash-bargaining solution (12), the efficient-separation condition (13), the zero-profit condition $V_i(Z) = 0$, and the value functions (8)-(11).

**Baseline Calibration.** Table 4 shows the main parameter values of the model, which are calibrated to standard values in the literature. Parameters are chosen to be the same for
### TABLE 4. CALIBRATION OF THE MAIN PARAMETER VALUES IN THE MODEL

<table>
<thead>
<tr>
<th>Parameter/Value</th>
<th>Description</th>
<th>Source/Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preferences:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta = 0.9966$</td>
<td>Discount factor</td>
<td>Annual real interest rate $r = 4.17%$</td>
</tr>
<tr>
<td><strong>Matching technology and bargaining:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta = 0.5$</td>
<td>Elasticity of matching function</td>
<td>Micro studies</td>
</tr>
<tr>
<td>$\kappa = 0.31$</td>
<td>Matching efficiency</td>
<td>Average labor market tightness $\theta = 1$</td>
</tr>
<tr>
<td>$\alpha = 0.5$</td>
<td>Worker’s bargaining share</td>
<td>Hosios condition</td>
</tr>
<tr>
<td><strong>Aggregate productivity shocks:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$z_b = 0.98$, $z_g = 1.02$</td>
<td>Productivity in bad and good state</td>
<td>Shimer (2005)</td>
</tr>
<tr>
<td>$\pi_{gb} = \pi_{gb} = 1/24$</td>
<td>Transition probabilities</td>
<td>Krusell and Smith (1998)</td>
</tr>
<tr>
<td><strong>Match- and worker-specific productivity:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(x_{t+1}) = \rho \ln(x_t) + \varepsilon_t$</td>
<td>Process for match-specific productivity</td>
<td>Bils, Chang and Kim (2012)</td>
</tr>
<tr>
<td>where $\rho = 0.98$ and $\sigma_\varepsilon = 0.043$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$a_{\text{low}} = 0.575$, $a_{\text{high}} = 1.425$</td>
<td>Worker-specific productivity for low- and high-productivity workers</td>
<td>Difference of average log hourly wages below and above the median (CPS ORG data, 1980-2012)</td>
</tr>
<tr>
<td><strong>Internally calibrated parameters:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c_{\text{low}} = 0.20$, $c_{\text{high}} = 1.06$</td>
<td>Vacancy-posting cost for low- and high productivity workers</td>
<td>Average monthly job finding rate for low- and high-wage workers ($f_{\text{low}} = f_{\text{high}} = 0.31$)</td>
</tr>
<tr>
<td>$b_{\text{low}} = 0.41$, $b_{\text{high}} = 0.36$</td>
<td>Flow-value of unemployment for low- and high-productivity workers</td>
<td>Average monthly job separation rate for low- and high-wage workers ($s_{\text{low}} = 0.014$, $s_{\text{high}} = 0.007$)</td>
</tr>
</tbody>
</table>

Both groups of workers unless otherwise noted. The period length of the model is one month and the discount factor $\beta$ is set to match an annualized interest rate of $4.17\%$. The elasticity of the matching function $\eta$ is in accordance with estimates from micro studies and is set to $0.5$. The matching efficiency $\kappa$ is a free parameter in the model and chosen such that $\theta = 1$ on average. The worker’s bargaining power is set equal to the elasticity of the matching function in order to satisfy the Hosios condition. In the baseline calibration, I only allow for aggregate productivity shocks as source of aggregate fluctuations and thus set $\lambda = 0$ in all aggregate states. 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), and the transition probabilities are taken from Krusell and Smith (1998), which imply an average duration of recessions and expansions of two years.\footnote{The robustness checks reported in the Appendix Tables D.1, D.2 and E, show that the main results do not change much when I assume that recessions are of shorter duration than expansions.} The log of match-specific productivity is assumed to follow an AR(1) process with the autocorrelation coefficient of 0.98 as in Bils, Chang and Kim (2012). The standard deviation of innovations $\sigma_\varepsilon$ is set to the average across the four different groups in the same paper. The worker-specific productivities $a_i$ are set to match the group-specific average wages in the CPS ORG data.

The key challenge in the calibration of the model is how to set values of parameters...
that potentially depend on $a_i$. To impose discipline on the calibration, the flow-value of unemployment $b_i$ is set to match the average separation rate of low- and high-wage workers in the CPS ORG data, and the vacancy posting cost $c_i$ is set to match the average job finding rate for low- and high-wage workers. The main goal of the calibration exercise is to evaluate whether a model that fits the average separation and job finding rate for each group, can replicate the compositional changes in the pool of unemployed over the business cycle as documented in Tables 1 and 2.

**Results.** Panel B in Table 5 reports results for the baseline calibration of the model. The same filtering methods as for the empirical results are applied to the simulated time series. As is evident from the bottom of the table, the calibration strategy results in a lower flow-value of unemployment for high-ability workers. This is in line with two main observations: First, wages are generally replaced only up to a specified limit. In the U.S., the maximum unemployment benefit is binding for approximately 35% of the unemployed workers (see Krueger and Meyer, 2002). Second, $b_i$ also captures the utility derived from additional leisure during unemployment as well as consumption provided by additional home production, which is likely to be less than proportional to market ability, $a_i$. For these reasons, the ratio of $b_i$ to $a_i$ should be higher for the low-ability group.

This calibration, however, does not do well in capturing the documented facts, as it generates a pro-cyclical pre-displacement wage and a higher, not lower, cyclicity of separations for the low-ability types. The intuition for this failure is related to the cyclical behavior of the worker’s outside option. The efficient-separation equation (13), 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 $b_i$ 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 flow-value of unemployment $b_i$) is large relative to the non-constant term (the expected value in the next period) and thus $R_i$ changes more in response to an aggregate productivity shock. For this reason, separations tend to be more cyclical for low-ability workers. Appendix Table D.1 shows that this result holds for various calibrations of the main parameters of the model.
### Table 5. Comparison of Statistics from Data and Different Models

<table>
<thead>
<tr>
<th>Statistic:</th>
<th>A. Data (CPS ORG; NLSY79)</th>
<th>B. Baseline model</th>
<th>C. Alternative Calibration</th>
<th>D. Indiscriminate separation shocks ($\lambda$)</th>
<th>E. Credit-constraint shocks ($\gamma$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cyclicality of aggregate $^1$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>... log pre-displacement wage</td>
<td>2.74</td>
<td>-2.80</td>
<td>4.23</td>
<td>3.10</td>
<td>2.46</td>
</tr>
<tr>
<td>Cyclicality of group-specific</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>... log separation rates</td>
<td>$w_{\text{low}}$</td>
<td>$w_{\text{high}}$</td>
<td>$a_{\text{low}}$</td>
<td>$a_{\text{high}}$</td>
<td>$a_{\text{low}}$</td>
</tr>
<tr>
<td>... log job finding rates</td>
<td>-0.55</td>
<td>-0.66</td>
<td>-0.63</td>
<td>-0.31</td>
<td>-0.39</td>
</tr>
<tr>
<td>... log unemployment rates</td>
<td>0.78</td>
<td>1.39</td>
<td>1.17</td>
<td>0.68</td>
<td>0.77</td>
</tr>
<tr>
<td>... log reservation productivities</td>
<td>-</td>
<td>-</td>
<td>0.062</td>
<td>0.036</td>
<td>0.036</td>
</tr>
<tr>
<td>Cross-sectional statistics: $^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std(log wage changes)</td>
<td>0.27</td>
<td>0.27</td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
</tr>
<tr>
<td>AR(1) coefficient of log wages</td>
<td>0.99</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td>Group-specific parameters:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$b_i / a_i$</td>
<td>-</td>
<td>-</td>
<td>0.70</td>
<td>0.25</td>
<td>0.71</td>
</tr>
<tr>
<td>$\sigma_\epsilon$</td>
<td>-</td>
<td>-</td>
<td>0.043</td>
<td>0.043</td>
<td>0.037</td>
</tr>
<tr>
<td>$c_i$</td>
<td>-</td>
<td>-</td>
<td>0.20</td>
<td>1.06</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Notes: $^1$ The average pre-displacement wage is computed in the exact same way as in the empirical analysis, i.e. it is the average log wage from one year ago for those currently unemployed. All time-series in the model simulations are HP-filtered with a smoothing parameter of 900,000. The cyclicality is measured in the exact same way as in the empirical analysis (see the notes of Table 1 and 2). Sample size for data: 370 monthly observations. Sample size for model simulations: 2400 monthly observations. Note that the model data are not simulated at the individual level, but instead the transition matrices are used to compute the exact distribution of individuals across individual states for every month of the simulation.

$^2$ The cross-sectional statistics are obtained from the sample of job-stayers in the NLSY79. The std(log wage changes) corresponds to the estimates reported in row 4 of Table D.4. The AR(1) coefficient is estimated with the same sample, by regressing the log hourly wage on past year's log hourly wage and then converting the yearly AR(1) coefficient to a monthly frequency.

### 4.2 Alternative Calibration Strategy

Panel C in Table 5 shows the results for an alternative calibration strategy where it is assumed that the flow-value of unemployment is proportional to worker ability ($b_i = b a_i$) and the variance of match-specific productivity shocks is calibrated internally and set to match the average separation rates for each group.$^{40}$ The average flow-value of unemployment $b$ is set to 0.71 as in Hall and Milgrom (2008). As can be seen from the bottom of the table, this calibration strategy results in a standard deviation of match-specific productivity shocks $\sigma_\epsilon$ that is more than twice as large for the low-ability group, to match the higher average separation rate of this group. In line with the data, this model generates large counter-cyclical shifts in the pre-displacement wage and a higher cyclicality of separation rates for high-ability workers. In contrast to the baseline calibration, however, differences in the cyclicality of separations are not driven by differences in the cyclicality of reservation match productivities. Instead, the reason for the higher cyclicality of separations is that the density of matches with $x = R_i$ is

---

$^{40}$ This is essentially the calibration strategy used by Bils, Chang and Kim (2012).
The model is also successful in the sense that it predicts that the cyclicality of the job finding rate is similar across the two groups, whereas other explanations put forward in this section have difficulties in matching this fact.

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 a lower variance of match productivity shocks is to look at the variance of yearly wage changes in the data. If the variance of match productivity shocks differs across wage groups, we should observe differences in the variance of wage changes. However, as shown in Table 5, in the NLSY79 data, the variance of wage changes (conditional on staying at the same employer) is the same across the two wage groups, whereas - in the model - the standard deviation tends to be twice as high for the low-ability group. To be fair, the model fails at generating enough dispersion in wages for both types of groups but, as shown in the Appendix Table D.2, a calibration with a lower flow-value of unemployment ($b = 0.4$) and thus a higher dispersion of wages does little to change that conclusion. To sum up, while this alternative calibration of the model is successful at replicating the compositional changes in the data, a higher variance of match-specific productivity shocks for the low-ability group does not appear to be supported by the additional evidence from the NLSY79.

### 4.3 Indiscriminate Separation Shocks

Another reason why separations are more cyclical 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 countercyclical (see Davis, Haltiwanger and Schuh, 1996). If workers of different ability are randomly distributed across firms and plants, or even smaller units within a firm, 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

\[
\frac{d \ln s_{it}}{d \ln z_{it}} = \tilde{M}_{it} \frac{d \ln R_{it}}{d \ln z_{it}},
\]

where $\tilde{M}_{it}$ depends on the distribution of match-specific productivities $x$. See Appendix D.1 for details.

If the log wage in the model is decomposed into $w_{it}^a + w_{it}^x + w_{it}^z$, where $w_{it}^a$ is a worker-specific effect, $w_{it}^x$ a match-specific productivity effect and $w_{it}^z$ an aggregate productivity effect, then taking the difference filters out the worker-specific component, and one can show that $\text{Var}(d \log w_{it}) = \frac{2}{1 + \rho_x^z} \text{Var}(w_{it}^a) + \frac{2}{1 + \rho_z^z} \text{Var}(w_{it}^z)$, where $\rho_x^z$ and $\rho_z^z$ are the autocorrelation coefficients of $w_{it}^a$ and $w_{it}^z$.

See Hornstein, Krusell and Violante (2011) for an elaborate analysis of wage dispersion in search models. Appendix D.4 also shows that this conclusion holds when allowing for non-proportionality in the flow-value of unemployment. In particular, it shows that hybrids of the baseline and the alternative calibration strategy cannot match the compositional shifts among the unemployed without a significant departure from the equal variance of match-specific productivity shocks of low- and high-ability workers.
average separation rates (high-ability workers). A simple way of modeling such shocks is to introduce an exogenous plant death shock, which in the model with one employee per firm is equivalent to the exogenous separation shock $\lambda$ described above in the model.

The key issue here is how to calibrate the magnitude of the shock to $\lambda$. The Business Employment Dynamics (BED) from the BLS and the Business Dynamics Statistics (BDS) from the Census contain information on the rate of job destruction at dying establishments. As shown in the Appendix Table D.5, there is a substantial fraction of jobs destroyed at dying establishments, but it does not appear to fluctuate that much. One concern here is that establishments die over the course of several quarters, and thus these statistics may understate the volatility of job destruction at dying firms. An alternative data source are the Mass Layoff Statistics from the BLS, which record firm-level layoffs of 50 or more in a given month. This includes mass layoffs at firms that are not dying, and thus one should consider these layoffs as a clear upper bound for layoffs at dying firms. It is important to note, however, that mass layoffs may be associated with the death of smaller units within firms and thus may also be modelled as an indiscriminate separation shock. To get an upper bound on the importance of indiscriminate separation shocks, I thus calibrate $\lambda$ in accordance with the average and the volatility of the mass layoff rate shown in Table D.5 and set $\lambda$ to 0.27% in recessions and to 0.11% in expansions.

This calibration of the model does a good job at capturing the counter-cyclicality of the pre-displacement wage and the higher cyclicity of separations for high-ability workers, for the reason mentioned above. As shown in the Panel B of the Appendix Table D.2, the success of the model depends crucially on the relative variance of aggregate productivity shocks $z$ and indiscriminate separation shocks $\lambda$: If the model is calibrated to the volatility of job destruction at dying firms in the BDS and BED data, the model still generates a counter-cyclical pre-displacement wage but of a smaller magnitude than in the data, whereas a model without aggregate productivity shocks generates too much counter-cyclicality in the pre-displacement wage. Overall, these results suggest that indiscriminate separation shocks can explain a substantial part of the documented compositional shifts.

4.4 Credit-Constraint Shocks

Recessions are often periods where access to credit becomes more difficult. 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?\textsuperscript{45}

To more formally evaluate these questions, I incorporate credit-constraint shocks into my benchmark model. I use a short-cut by assuming that in recessions, worker-firm matches face a constraint to produce cash flows above some number $-\gamma$:

$$zxa_i - w_i(Z, x) \geq -\gamma,$$

where $\gamma$ is stochastic and thus the aggregate state is $Z = [z, \lambda, \gamma]$. Naturally, workers may be willing to deviate from the Nash-bargained wage and take a wage cut in order to remain employed. Therefore, wages are assumed to satisfy the Nash-bargaining solution $w_i^{NB}(Z, x)$ as long as the cash-flow constraint (15) is met, but otherwise adjust to meet the constraint:

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

If the cash-flow constraint cannot be met at any acceptable wage for the worker, worker-firm matches will dissolve.\textsuperscript{46,47}

I use the same parameter values as for the baseline calibration above, and set $\gamma$ to 0.15 in recessions and assume it to be non-binding in expansions.\textsuperscript{48} This calibration yields a counter-cyclical pre-displacement wage and higher cyclicality of separations for high-ability workers in line with the data. Given the reduced form nature of this model, it is difficult to calibrate the size of the shock but, as shown in the Appendix Table E, the model produces a counter-cyclical pre-displacement wage for various calibrations of the size of the shock.

\textsuperscript{45}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. Moreover, Chodorow-Reich (2014) provides evidence for strong effects of credit tightening on firm-level employment in the Great Recession.

\textsuperscript{46}This process of wage setting is essentially the opposite of how minimum wages are sometimes introduced in search-matching models, where firms would unilaterally separate from the worker if the firm’s share of the surplus is negative at the minimum wage. See, e.g., Flinn (2006) and Brochu and Green (2013) for search-matching models with minimum wage constraints.

\textsuperscript{47}The assumption here is that wages are renegotiated in 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. See, for example, Michelacci and Quadrini (2009) and Guiso, Pistaferri and Schivardi (2013) who show that workers extend credit to constrained firms by accepting backloaded wage-tenure profiles. Note, however, that the model here is not inconsistent with back-loaded wage profiles, for the model allows the current wage to deviate from the Nash-bargained wage. Moreover, Chodorow-Reich (2014) provides credible evidence that tightening credit-constraints affect firm-level employment, suggesting that there are limits to intertemporal trading.

\textsuperscript{48}The average cash flow in this economy is about 1.2% of average labor productivity. It may be argued that these constraints are very tight as a firm would need just about one year of average productivity 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.
The important insight is that in the baseline model without cash-flow constraints, each worker-firm match produces negative cash flows at the efficient reservation productivity level. As shown in the Appendix E, the firm’s cash flows at the reservation productivity level \( R_i(Z) \) can be written as:

\[
CF_i(Z, R_i(Z)) = -\beta E \left[ \max \{(1 - \alpha)S_i(Z', x'), 0\} \mid Z, R_i(Z) \right]. \tag{17}
\]

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 bargaining 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 for two reasons: First, because high-ability workers have a lower flow-value of unemployment \( b_i \) relative to market ability \( a_i \), the reservation match productivity \( R_i(Z) \) is lower. Second, match surpluses at a given level of \( x \) and \( z \) are increasing in ability, which implies that cash flows are more negative for high ability workers even if \( R_i(Z) \) were the same for both types.\(^{49}\) For these reasons, cash flows are more negative for marginal matches with high-ability workers and thus they are more sensitive to a tightening of credit, as the constraint is binding at higher (i.e., less tight) levels of \( \gamma \). In other words, marginal high-ability workers are the first ones to go when wages are cut due to a binding cash-flow constraint.\(^{50}\)

**Discussion.** One may argue that the model is at odds with the fact that quits tend to fall in recessions (see Akerlof, Rose and Yellen, 1988), as well as results shown in the Appendix Table C.1 that suggest that my empirical findings are driven mainly by layoffs. However, it is misleading to label – in the model – separations driven by tightening constraints as quits, as the model takes as given that firms demand a wage cut when facing tightening credit constraints. A more refined wage bargaining protocol with small bargaining costs would result in firms firing workers in the anticipation that workers would not accept a wage cut. This is also consistent with McLaughlin (1991) who defined layoffs as "firm-initiated separations, result[ing] from censored wage cuts" (p.6).

Another potential concern may be that, in the model, firms are small in the sense that

\(^{49}\)To quantitatively separate the importance of the two channels, Appendix Table E provides also results where the cash flow constraint is proportional to worker ability \( a_i \) (instead of being the same across worker types). The results suggest that the non-proportionality in replacement rates (i.e., the first reason) is an important contributor to the results in the model with cash flow constraints, as the counter-cyclicality of the pre-displacement wage is substantial for various calibrations of the size of the proportional shock.

\(^{50}\)The results in Table 5 show that, as for the baseline model, the differences in the cyclicity of separation rates are mainly driven by differences in the cyclicity of (worker) reservation productivities.
they only have one employee. It may be argued 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 level and the firm might prefer to lay off workers with a low future expected surplus (i.e., low-ability workers). Notice, however, that in a multi-worker firm, each worker-firm relationship has a shadow value of relaxing the cash-flow constraint today as well as in future states where it is binding. This shadow value is increasing more than proportionally with the ability of the worker, because the reservation match productivity is set to a lower level where cash flows are more negative not only today but also in the near future because of serially correlated match-specific productivity. Therefore, it should be optimal for a multi-worker firm to fire these marginal high-ability workers rather than marginal low-ability workers if the firm anticipates binding cash-flow constraints that last more than one period. In addition, if there are small fixed firing costs per worker, then the firm would prefer getting rid off high-ability workers, even if cash flows were fully proportional to ability. For these reasons, one should expect the main mechanisms in my model to be operative in a multi-worker firm setup. Of course, ideally, one should set up a multi-worker firm model to investigate the quantitative effects of cash-flow constraints on the cyclicality of separations for low- and high-ability workers. However, such a model 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.

Finally, one may wonder whether the theory is consistent with the magnitude of the compositional shifts for each of the recessions covered in the empirical analysis. In particular, the Figures 3 and 4 show that the magnitude of the shift was not unusually strong during the Great Recession of 2007-2009, whereas indicators, such as bank’s commercial lending standards or credit spreads, suggest a credit tightening that was much stronger than in any other recession. From this view point, it seems difficult to argue that credit-constraint shocks explain the compositional shifts in all major recessions covered in the empirical analysis. It is important to note, however, that, quantitatively, the model predicts shifts in the composition of unemployed that are strongest at intermediate levels of the shocks (see Appendix Table 51).

51 Simulation results for the benchmark model without cash flow constraints show (see Appendix E) that – over the course of a recession of average length – cumulated cash flows are much more negative and disproportionate to the expected future surplus for marginal matches with high-ability workers.

52 Stole and Zwiebel’s (1996) intrafirm bargaining game would thus be a good starting point to modelling firm-level cash-flow constraints, but is further complicated by the presence of low- and high-ability types.

53 Indeed, the out-of-sample prediction of the compositional changes for the years 2007-2012 closely matches the actual value of the average pre-displacement wage shown in Figures 3 and 4 for this period.

54 E.g., Gilchrist and Zakrajsek (2012) construct an excess bond premium, which sharply increased in 2007-08 and to a lesser degree in other recessions, except the one in 1990-91, where it shows no movement. Commercial lending standards appear to have increased in all major recessions since 1973 except the one in 1980 (see Lown and Morgan, 2006, and Gilchrist and Zakrajsek, 2012).
E). The reason is that small shocks only affect marginal matches with high-ability workers, whereas larger shocks affect matches with workers of all types. Therefore, testing the implications of this model extension with time-series data on firm-level financial constraints is challenging, though it is certainly difficult to reconcile the theory with recessions that did not show any signs of credit tightening.\footnote{For the same reason, it is also challenging to test the predictions of the theory with industry- or firm-size-class level data on firms’ financial constraints. In the March CPS data, I find that the compositional effects are somewhat stronger for those previously employed by a large firm, but this may also capture other differences between small and large firms. In particular, I find that those separated from large employers are – on average – more negatively selected in terms of the previous wage compared to those separated from small employers. Therefore, plant death shocks will lead to larger changes in the previous wage of those previously employed at a large employer.}

A promising avenue for future research is to directly test the theory with matched employer-employee data. In particular, one could use the identification strategy in Chodorow-Reich (2014) who estimated the effect of credit tightening on firm-level employment, using information on the pre-crisis banking relationships to instrument for the credit shock at the firm level. It would be interesting to extend his analysis with matched employer-employee data and estimate the effect of credit tightening on the firm-level composition of layoffs in terms of directly observable skill measures or within-firm wage rankings prior to the credit shock. Moreover, such a firm-level analysis allows for a test of the non-monotonic relationship between credit-constraint shocks and their compositional effects.

4.5 Theories Based on Other Sources of Heterogeneity

All explanations for the documented facts discussed so far focused on a model with worker heterogeneity in terms of productivity as the main source of wage dispersion across workers. This section discusses a number of alternative theories with other sources of wage dispersion that may be consistent with the empirical patterns documented in this paper.

Heterogeneity in Other Parameters. One may argue that the empirical results are driven by a higher cyclicality of separations for workers with a higher flow-value of unemployment $b_i$. In a model with Nash-bargaining, these workers also get paid a higher wage due to the higher value of the outside option. While this leads to more cyclical separations for high-wage (=high-$b$) workers (see the Appendix Table D.3 for simulation results), the fundamental difficulty with this approach is that it results in a higher average separation rate for the high-wage workers, which is in sharp contradiction with the evidence in Table 2. Another source of heterogeneity may be that some workers are better at extracting surplus from a working relationship, captured by a higher bargaining share $\alpha$. However, the simula-
tion results in Appendix Table D.3 show that in such a model the cyclicality of separations for these workers tends to be lower, not higher, compared to workers with a lower bargaining share \( \alpha \). The reason is that a higher \( \alpha \) tends to make the outside option of the worker more pro-cyclical and thus separations less counter-cyclical.

**Match-Specific Productivity as the Only Source of Wage Dispersion.** What about a model where workers are homogenous and differ only in terms of the current match-specific productivity \( x \)? In the presence of persistent match productivity, such a model may produce a counter-cyclical pre-displacement wage, as workers with a high draw of match productivity \( x \) in the past become more likely to separate in recessions when the reservation match-productivity threshold increases. However, as the simulation results in Appendix Table D.3 show, the magnitude of these compositional shifts is very small, even when contrasted to the shifts with respect to the residual wage only.

**Compensating Differentials for Unemployment Risk.** One may argue that wages compensate for the risk of layoff and thus that such a model could generate the patterns in the data. This explanation faces several challenges: First, on average, layoff risk is higher for low-wage workers, even when controlling for observable characteristics. Second, the cyclicality of separations in Table 2 is measured in log terms, which is what matters for the compositional changes among the unemployed. However, in levels, the separation rate is only slightly more cyclical for high-wage workers and thus it seems unlikely that this would account for a large wage differential between low- and high-wage workers.\(^{56}\) Third, I set up and calibrate a simple model of compensating differentials and find that even when attributing all cyclical layoff risk to one type of job (and assuming a constant layoff risk for the other type of job), the wage premium for the job with cyclical risk is less than one percent and thus, the compositional shifts in terms of the pre-displacement wage in this model are tiny.\(^{57}\)

**Wage Rigidity.** Another potential explanation for the empirical results in this paper could be 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. One problem with this explanation is that it does not rely on worker heterogeneity in terms of productivity, and thus cannot explain why the pool of unemployed worker sorts towards workers with observable high-wage characteristics in recessions.

\(^{56}\) Appendix G.1 provides estimates of average separation rates in periods of low and high unemployment. 

\(^{57}\) See Appendix H for details.
Nevertheless, to assess whether such a model can potentially explain the empirical results, I introduce wage rigidity into the baseline model above by assuming that wages are Nash-bargained in a staggered fashion as in Gertler and Trigari (2009).\textsuperscript{58} The results in the Appendix Table F show only very small compositional shifts towards high-wage workers in recessions. One reason is that match-specific shocks lead to inefficient separations among high-wage workers even in good times and thus, the cyclicality of separations is not much more cyclical for high-wage workers than for low-wage workers. A second reason is that overall wage dispersion in the model is modest, and thus, even if high-wage workers have more cyclical separation rates, this translates into small changes in the composition of the unemployed in terms of the average pre-displacement wage. The main reason for the small amount of wage dispersion is that the model features a lot of inefficient separations, and increasing wage dispersion, by raising the dispersion of match-specific shocks, results in a counter-factually high average separation rate.

5 Conclusion

This paper provides a new fact 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. These shifts are driven by the higher cyclicality of separations for high-wage workers, and not by more cyclical job findings of these workers. Moreover, the compositional shifts are associated with both observed as well as unobserved factors in the previous wage but the unobserved factors are not driven by employer size. Finally, the magnitude of the compositional changes over the business cycle is substantial and much larger than the compositional changes among the employed.

The findings have important implications for models of aggregate fluctuations of the labor market, as shifts towards high-ability workers in recessions aggravate the apparent lack of an amplification mechanism on the hiring margin in the standard search-matching model. The findings thus pose an additional challenge to the recent literature on the "unemployment volatility puzzle" (see Shimer, 2005), at least to the extent that these compositional shifts are associated with aggregate productivity shocks. It is possible that other shocks such as cyclical credit constraints also limit the extent to which firms hire in recessions and thus provide for a channel of amplification on the hiring margin.\textsuperscript{59} The findings also suggest that the welfare

\textsuperscript{58}See the Appendix F for the details of the model. It is important to note that my model differs from Gertler and Trigari who assume exogenous separations and focus their attention on the hiring margin.

\textsuperscript{59}Cash-flow constraints may affect the hiring behavior of firms if match-specific productivity is sufficiently low at the start of the employment relationship. However, it is not straightforward how to discipline the calibration of the initial distribution of match-specific productivity (i.e., at the time of the match) and thus
costs of business cycles are more equally shared between high- and low-ability workers, as high-ability workers face more cyclical unemployment risk than previously assumed. To the extent that high-ability workers are better able to self-insure against unemployment shocks (see, e.g., Mukoyama and Sahin, 2006), the findings also imply a lower overall welfare cost of business cycles. For the same reason, one would expect shifts towards high-ability workers to attenuate the need for counter-cyclical unemployment insurance.\textsuperscript{60} To conduct a proper welfare analysis, however, it is important to model the savings and consumption choices of the employed and unemployed. I leave this important task for future research.\textsuperscript{61}

Given the importance of the findings, the paper evaluates a number of theories that can potentially explain the documented facts. A search-matching model with endogenous separations and worker heterogeneity has difficulty in generating shifts towards high-ability workers in recessions, unless one assumes a lower variance of match-specific shocks for high-ability workers, which is not supported by additional facts documented in this paper. Another explanation that can account for a substantial part of the compositional shifts is related to the fact that plants die at higher rates in recessions. Plant death should affect all workers indiscriminately of type and thus improves the overall quality of the pool of unemployed, whose distribution is skewed towards low-skilled workers. Finally, the paper points towards cyclical credit constraints as an additional explanation of the documented facts, though the theory cannot account for shifts towards high-wage workers in recessions that do not show any signs of credit tightening and thus is unlikely to be the only explanation for the facts documented in this paper.

An important avenue for future research is to extend my empirical analysis with other data sources. Matched employer-employee data is particularly promising as it allows us to determine directly the importance of plant death for separations. Moreover, it makes it possible to refine the analysis with the NLYS79 data by separately identifying firm and worker fixed effects. Finally, matched employer-employee data could also be used to directly test for the importance of credit frictions for the compositional changes in the pool of unemployed, if balance sheet information on the firm side or information on firm-level banking relationships is obtained.

\textsuperscript{60}See, e.g., Schmieder, von Wachter and Bender (2012) who show that the disincentive effects of unemployment insurance (UI) are somewhat smaller in recessions, whereas the consumption smoothing benefits are larger as unemployed workers are more likely to exhaust UI in recessions. Similarly, shifts towards high-wage workers may also reduce the Keynesian multiplier effect of UI (see McKay and Reis, forthcoming, who analyze the multiplier effect of UI in a model with incomplete markets).

\textsuperscript{61}Appendix I explores the implications for the welfare costs of business cycles within a simple reduced-form model that directly calibrates the consumption levels of the employed and the unemployed. While there are some obvious limitations to this exercise, one should expect that the main results should carry over - at least qualitatively - to a general equilibrium model with incomplete markets.
References


