Separations, Sorting, and Cyclical Unemployment[†]

By Andreas I. Mueller*

This paper establishes a new fact about the compositional changes in the pool of unemployed over the US business cycle. Using microdata from the Current Population Survey for the years 1962–2012, it documents that in recessions the pool of unemployed shifts toward workers with high wages in their previous job and that these shifts are driven by the high cyclicality of separations for high-wage workers. The paper finds that standard theories of wage setting and unemployment have difficulty in explaining these patterns and evaluates a number of alternative theories that do better in accounting for the new fact. (*JEL* E24, E32, J31, J63, J64)

This paper establishes a new fact about the compositional changes in the pool of unemployed over the US 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 toward 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 toward 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 show that the compositional shift is almost entirely driven by separations. The reason is that separations are substantially more cyclical for

high-wage workers, whereas the cyclicality of job finding rates is similar across wage groups.

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 toward low-ability workers, shifts toward high-ability workers in recessions lead to a dampening of productivity shocks.[1] The reason is that when unemployment shifts toward 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 toward high-ability workers in recessions may dampen the response of hiring to aggregate productivity shocks.[2]

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 suggest that it is not sufficient to control for demographic characteristics as the pool of unemployed shifts toward high-residual wage workers in recessions. The compositional changes may affect— among others—the measurement of the cyclicality of search intensity, the cyclicality of reservation wages, the cyclicality of wages of newly hired workers, as well as the cyclicality of the effects of unemployment insurance or job training programs.[3,4]

Given the importance of the fact documented in the first part of the paper, the second part tries to explain it. The paper starts by evaluating a number of standard theories of wage setting and unemployment, including a search-matching model with match-specific productivity and endogenous separations, a model with rigid wages and inefficient separations, as well as a model with compensating differentials for unemployment risk. These models, however, predict compositional shifts either in the opposite direction of or tiny in magnitude compared to the shifts in the data, because separations of high-wage workers relative to separations of low-wage workers are not cyclical enough and because these models generate little dispersion in pre-displacement wages.

The paper also evaluates a search-matching model with endogenous separations and worker heterogeneity in productivity. This model naturally produces more dispersion in pre-displacement wages. It is also motivated by the fact that the shifts

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

[2] Online Appendix G.1 compares steady state elasticities of the aggregate job finding rate in a search-matching model with exogenous shocks to separation rates. 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.

[3] For example, Card, Kluve, and Weber (2015) find that active labor market programs tend to be more effective in recessions and note that this may be driven by changing characteristics of program participants.

[4] See online Appendix K for details. Also, Baker (1992) and Kroft et al. (2016) find that the cyclicality of unemployment duration/job finding is not affected by composition bias. The reason for this finding is not the absence of compositional shifts but rather the fact that job finding rates do not differ much across groups.

documented in the CPS data can be attributed to a large extent to observable worker characteristics and are not driven by firm-size effects, and additional evidence from the National Longitudinal Survey of Youth 1979 (NLSY79) that the compositional changes are associated with permanent worker effects rather than transitory effects in pre-displacement wages. In the baseline version of this model, I match the average separation rates for low- and high-wage workers, by allowing the flow values of unemployment to differ across worker types. This calibration, however, generates shifts toward low-ability workers in recessions, which are in the opposite direction of the data. I examine several extensions of this model, of which two stand out.

The first successful extension allows for the variance of match-specific productivity shocks to be lower among high-ability workers. This model predicts large shifts toward high-ability workers in recessions as well as a high cyclicality of separations for high-wage workers, because the calibration increases the density of matches at the separation threshold for high-ability workers and thus changes in the threshold generate larger responses for these workers. This model also matches the fact that the cyclicality of job findings tends to be similar across wage groups, which is a challenge for models with heterogeneous workers. The main reason is that, in contrast to the baseline model with worker heterogeneity, this calibration preserves the proportionality of flow values of unemployment to worker productivity.

A second promising explanation 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 in recessions, which produces more cyclical separations for high-ability workers and shifts toward high-ability workers in line with the data. The intuition for this finding is that—in the absence of constraints—firms are willing to pay workers above current match productivity if they are compensated by positive expected future cash flows. If firms, however, face a constraint on their cash flows, workers and firms may separate even if it is in the interest of both parties to continue the relationship. In the model, marginal matches with high-ability workers generate more negative cash flows and thus are more sensitive to a credit tightening.

The paper concludes by discussing remaining weaknesses of the two leading explanations and additional evidence that may be able to distinguish between them. In short, the first extension mentioned above is successful in matching the relevant facts in the paper, but it is not entirely clear why the process for match-specific productivity should differ across worker types. The theory based on cyclical credit constraints appears to be inconsistent with recessions that do not show any signs of credit tightening, though, in general, testing the theory with time series data is difficult as the magnitude of the compositional shifts is not monotonically increasing in the size of the shock. The paper formulates a direct test based on Chodorow-Reich (2014) that allows to better assess the importance of the credit shocks for compositional shifts among the unemployed.

I. Related Research

The empirical patterns may appear to contradict findings from a related literature on the cyclicality of real wages. Specifically, Solon, Barsky, and Parker (1994) documented that the measured cyclicality of aggregate real wages is downward biased,

because the typical *employed* person is of higher ability in recessions. Hines, Hoynes, and Krueger (2001), however, showed that Solon, Barsky, and Parker's result relies on the weighting of aggregate real wages by hours worked. With unweighted wage data, composition bias has almost no effect on the cyclicality of real wages, suggesting that it is not the composition of the employed that changes over the business 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 toward high-wage workers in the pool of unemployed are fully consistent with small shifts toward 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 analyzes *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 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 cyclicality of worker flows for different wage groups. These equations reveal that it is important to assess the cyclicality of all group-specific worker flows and to assess the cyclicality of the composition of the labor force, before making 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 and documents in detail the compositional changes both in terms of observable worker characteristics and residual wages.

The empirical analysis in this paper is also related to a recent paper by Elsby, Hobijn, and Sahin (2015) who study the role of labor force participation for unemployment fluctuations. They find that shifts toward workers with strong labor force attachment in recessions can account for one-third of unemployment fluctuations, as these workers are less likely to transition from unemployment to out of the labor force.[5] Their analysis is complementary to the analysis in my paper because they measure labor force attachment by labor force status from one year ago, whereas my analysis focuses on compositional changes in terms of the pre-displacement wage

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[5] See also Krusell et al. (2015) who set up a three-state model of the labor market to study gross worker flows. Their model predicts compositional shifts toward more attached workers in recessions, generating pro-cyclical flows from unemployment to out of the labor force as in the data.

Month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Interview	1	2	3	4									5	6	7	8
				Wage												Wage

FIGURE 1. CPS PANEL STRUCTURE BY MONTH AND INTERVIEW NUMBER

and is conditional on being employed one year ago. It is important to note, however, that my results remain unchanged when including in the sample those unemployed or out of the labor force one year ago and predicting their wage based on observables. This suggests that compositional changes in terms of labor force attachment are not important for the shifts toward high-wage workers documented in this paper.

II. Data Sources

The main empirical analysis in this paper is based on micro data from the CPS, which is the main labor force survey for the United States. The main reason for using the CPS is the large sample size, as my analysis focuses on the relatively small subsample of unemployed. The CPS 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. Labor force status is recorded in each month, whereas weekly hours and earnings are collected only in the fourth and eighth interview of the survey, referred to as the Outgoing Rotation Groups (ORG).

The main focus of the empirical analysis is on the wage of those who lose their job and become unemployed, and thus I restrict my sample to 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.[6] I restrict the sample to private sector workers aged 16 to 64 with positive years of potential experience and follow Lemieux (2006) in the construction of the hourly wage variable. The sample covers the years 1980 to 2012 and the sample size is 1,203,543 individuals, of which 79,463 experienced at least 1 month of unemployment in interview months 5–8.[7]

The sample excludes unemployed individuals who have been unemployed for more than 12 months, but according to official statistics of the Bureau of Labor Statistics (BLS) the fraction of those with unemployment durations above 1 year never exceeded 13.3 percent in the period before 2008 and thus the constraint imposed by the sample-selection criterion is relatively minor. More recently, the share of those unemployed longer than 12 months increased dramatically to as much as 31.2 percent in 2011, and thus, the results for the later period have to be taken

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[6]The concern is that wages for new hires are more responsive to the business cycle. See, e.g., Bils (1985) and Haefke, Sonntag, and van Rens (2013).

[7]The CPS does not follow individuals who move out from an address and thus, similar to Bleakley, Ferris, and Fuhrer (1999), I adjust the survey weights to account for attrition based on observable characteristics.

with some caution.[8] The sample also excludes those out of the labor force at the time of the fourth interview, which is why I turn to additional data sources.

I also use 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 CPS ORG sample based on demographic characteristics. These data are fully representative of the population of unemployed workers, including the long-term unemployed and those who enter unemployment from out of the labor force. I also extend the analysis with data from the CPS March supplement, which is available since 1962 and faces no issues related to attrition as it has backward looking information on wages in the prior year. The CPS March supplement, however, is only available once per year and thus does not allow for the analysis of worker flows. See online Appendix A for further details.

Finally, I use data from the NLSY79 for the years 1979–2012, 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 biannual basis for the period 1994–2012. Information on labor force status is recorded at a weekly frequency throughout the sample period, even in the later period where interviews were at biannual frequency. 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 ten years of valid wage data. 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 6,923 individuals and 193,467 yearly observations on labor force status.[9]

III. Empirical Analysis

It is well known that the cyclical volatility of unemployment is higher for low-skilled and younger workers. Moreover, Solon, Barsky, and Parker (1994) 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 toward low-skilled workers in recessions (see, e.g., Pries 2008). However, as shown below, these facts may be fully consistent with compositional changes in the pool of unemployed toward high-skilled workers in recessions. In what follows, I 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 direct evidence on the composition of the unemployed over the US business cycle.

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[8] Data on self-reported duration, however, are likely to overestimate true duration in the more recent period (see Elsby et al. 2011).

[9] To increase the sample size, the pool of unemployed is defined as those unemployed at some point in a given calendar year weighted by their duration of unemployment.

A. *Measurement*

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

$$(1) \qquad \phi_{it}^U = \frac{\phi_{it}^L U_{it}}{\phi_{it}^L U_{it} + (1 - \phi_{it}^L) U_{jt}} = \phi_{it}^L \frac{U_{it}}{U_t},$$

where U_{it} is the unemployment rate of group i, U_{jt} is the unemployment rate of group j (the complement of group i), and ϕ_{it}^L is the fraction of group i in the labor force. Changes in ϕ_{it}^U thus can be attributed to changes in the proportion of the group-specific unemployment rate *relative* to the aggregate unemployment rate U_t, 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 toward low-skilled workers in recessions, because low-skilled workers also have a higher average unemployment rate and thus 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) yields an equation for the changes in the share of group i among the unemployed:

$$(2) \qquad d\phi_{it}^U = \phi_{it}^U(1 - \phi_{it}^U)\left[d \ln U_{it} - d \ln U_{jt}\right] + \frac{\phi_{it}^U}{\phi_{it}^L} \frac{1 - \phi_{it}^U}{1 - \phi_{it}^L} d\phi_{it}^L.$$

Online Appendix B derives an equation for changes in the share of group i among the employed:

$$(3) \quad d\phi_{it}^E = -\phi_{it}^E(1 - \phi_{it}^U)\frac{U_t}{E_t}\left[\frac{\phi_{it}^U}{\phi_{it}^E} \frac{1 - \phi_{it}^E}{1 - \phi_{it}^U} d \ln U_{it} - d \ln U_{jt}\right] + \frac{\phi_{it}^E}{\phi_{it}^L} \frac{1 - \phi_{it}^E}{1 - \phi_{it}^L} d\phi_{it}^L.$$

Comparing equations (2) and (3), it is easy to see that if ϕ_{it}^U is equal to ϕ_{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 ϕ_{it}^U is sufficiently different from ϕ_{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 toward 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 of group i into

$$(4) \qquad\qquad dU_{it} \approx U_{it}^{ss}(1 - U_{it}^{ss})[d \ln s_{it} - d \ln f_{it}],$$

where $U_{it}^{ss} = \frac{s_{it}}{s_{it} + f_{it}}$ is the flow steady state unemployment rate for group i and $E_{it}^{ss} = 1 - U_{it}^{ss}$ the flow steady state employment 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

$$(5) \qquad\qquad d\phi_{it}^{U} \approx \phi_{it}^{U}(1 - \phi_{it}^{U}) \begin{bmatrix} (1 - U_{it}^{ss})[d \ln s_{it} - d \ln f_{it}] \\ -(1 - U_{jt}^{ss})[d \ln s_{jt} - d \ln f_{jt}] \end{bmatrix},$$

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 separation and job finding rate of the complement group j. Therefore, one can conclude from the differences in the changes in the group-specific log separation and job finding rates, weighted by the steady state employment rates $(1 - U_{it}^{ss})$, which margin is 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.

B. *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, 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 the correlation tends to be positive.[10]

To evaluate more systematically, the extent to which the composition of the pool of unemployed sorts toward high-wage groups in downturns, I turn to the CPS ORG

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[10] Online Appendix B provides direct evidence on the ratios of employment and labor force participation rates, which tend to go in the same direction as for the unemployed but on a much smaller scale.
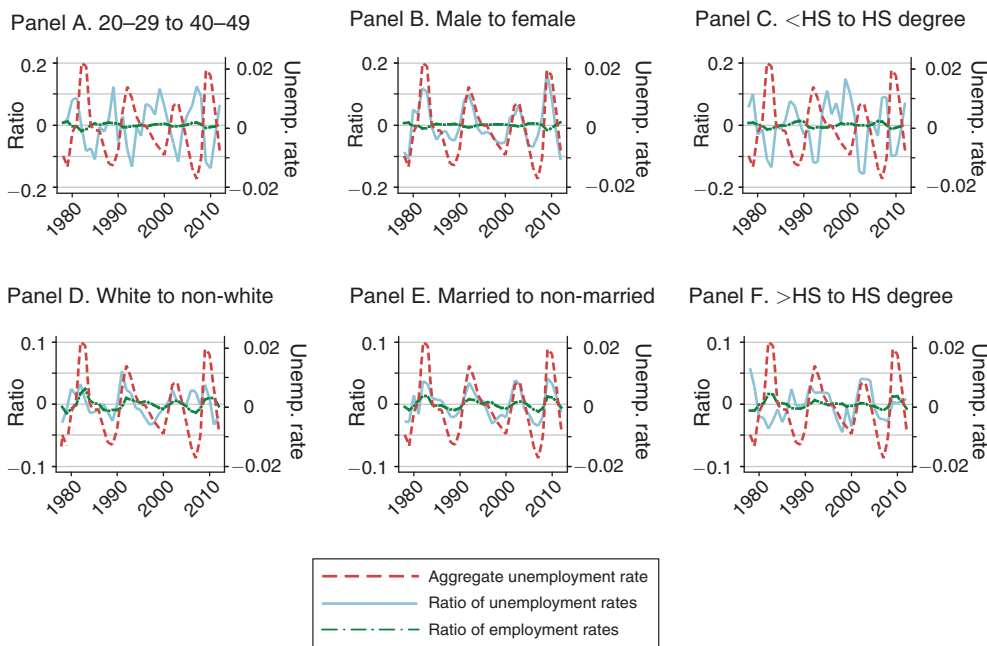
FIGURE 2. RATIOS OF GROUP-SPECIFIC UNEMPLOYMENT AND EMPLOYMENT RATES

Note: All series are yearly averages, HP-filtered with smoothing parameter 100.

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 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 four but unemployed in interview eight 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 0.59). 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 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

Panel A. Raw wage

Panel B. Wage rank

Panel C. Mincer-residual
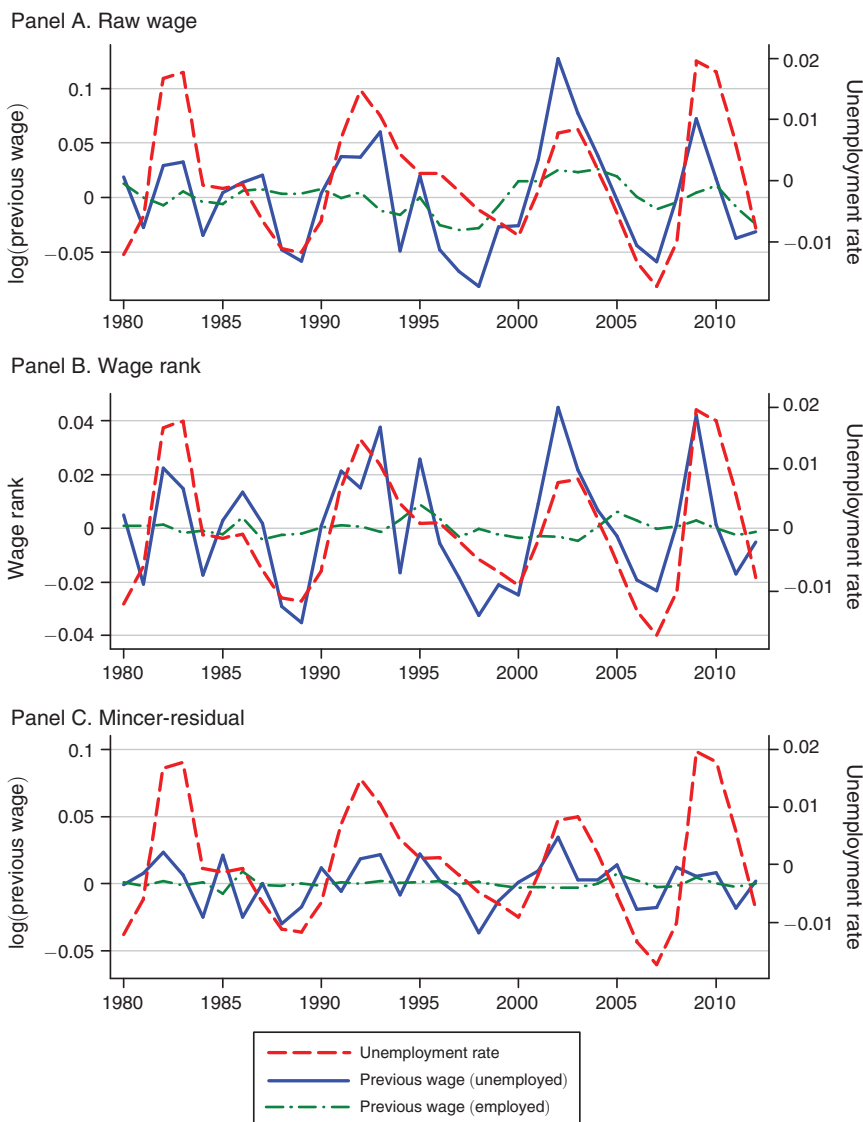
Figure 3. Average Wage from the Previous Year by Employment Status in the Matched CPS ORG Sample, 1980–2012

Note: All series are yearly averages, HP-filtered with smoothing parameter 100.

dataset (the rank in the wage distribution in a given year is defined by lining up all individuals according to their current wage from the lowest to the highest on the unit interval). If wage compression drives the patterns in 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 unemployment rate. The correlation coefficient is 0.67 (March CPS: 0.73), 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 1.5 percentage-point increase (March

Panel A. Raw wage

Panel B. Wage rank

Panel C. Mincer-residual
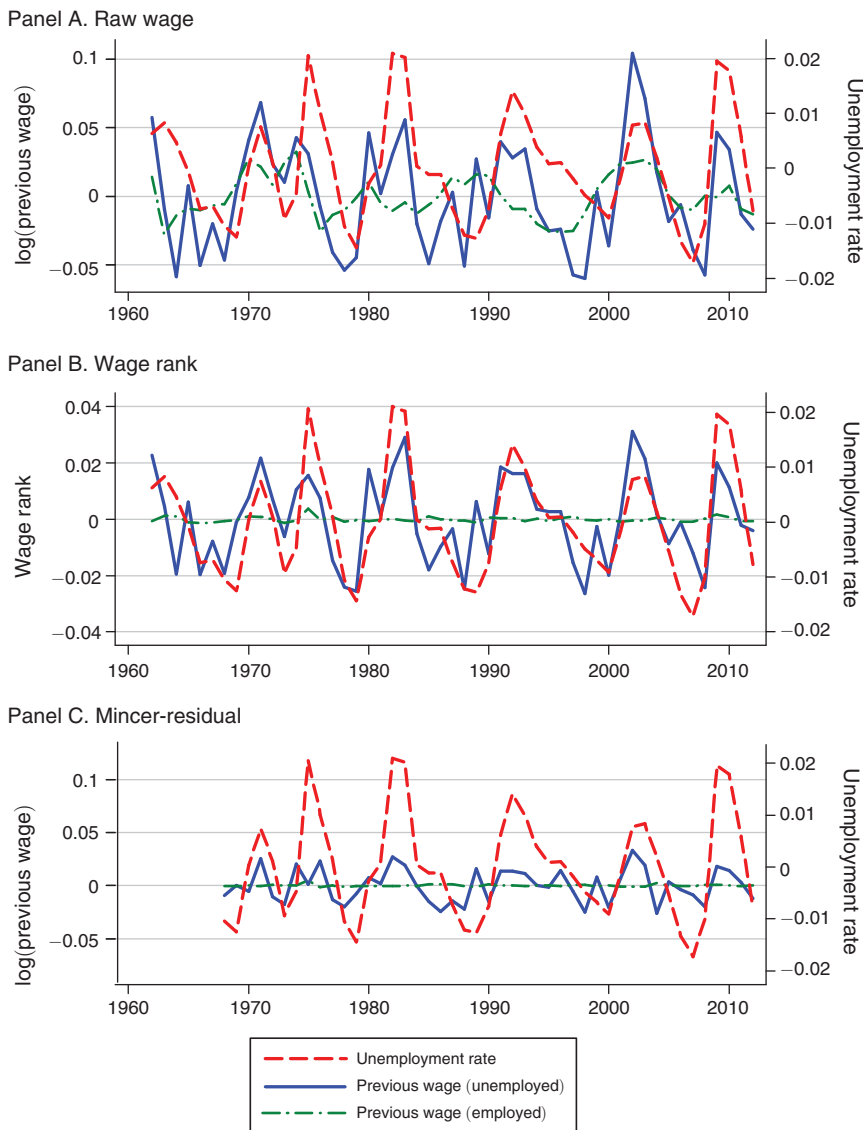
FIGURE 4. AVERAGE WAGE FROM PREVIOUS YEAR BY EMPLOYMENT STATUS IN THE CPS MARCH SUPPLEMENT, 1962–2012

Note: All series are yearly averages, HP-filtered with smoothing parameter 100.

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.[11] The average wage residual is still

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[11] By definition, the average wage residual is zero for each year for the full sample.

TABLE 1—COMPOSITIONAL CHANGES IN THE POOL OF UNEMPLOYED BY PREDICTED AND RESIDUAL
PRE-DISPLACEMENT WAGE

	Raw wage	Decomposition of predicted wage									Residual wage		
		Total	Experience	Educational attainment	Gender	Marital status	Race	State	Industry	Occu-pation	Total	Fixed effect	Transit. effect
Panel A. Matched CPS ORG													
Cyclicality	2.77	2.01	0.32	0.17	0.14	0.24	−0.03	0.12	0.69	0.37	0.75	—	—
	(0.51)	(0.38)	(0.08)	(0.10)	(0.03)	(0.04)	(0.04)	(0.10)	(0.10)	(0.10)	(0.20)		
Panel B. March CPS													
Cyclicality	2.59	1.64	0.23	0.10	0.12	0.23	0.02	0.05	0.70	0.19	0.95	—	—
	(0.28)	(0.19)	(0.04)	(0.06)	(0.02)	(0.02)	(0.01)	(0.06)	(0.08)	(0.08)	(0.13)		
Panel C. Monthly CPS													
Cyclicality	—	1.84	0.37	0.22	0.11	0.17	0.03	0.13	0.57	0.24	—	—	—
		(0.28)	(0.04)	(0.06)	(0.01)	(0.01)	(0.02)	(0.07)	(0.05)	(0.11)			
Panel D. NLSY79													
Cyclicality	2.08	0.93	−0.01	−0.08	0.24	0.20	0.10	—	0.20	0.28	1.16	0.77	0.38
	(0.45)	(0.36)	(0.06)	(0.15)	(0.06)	(0.04)	(0.02)		(0.12)	(0.14)	(0.57)	(0.16)	(0.48)

Notes: Newey-West corrected standard errors in parentheses. All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cyclicality is measured as the coefficient β in the regression $\log(w_t^u) - \log(w_t) = \alpha + \beta U_t + \varepsilon_t$, where w_t^u is the average wage from the previous year for those unemployed at time t, w_t 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 Statistics. 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 (the years 1962–1967 were not included as no information was available on industry in previous year), and the NLSY79 for the years 1979 to 2011.

strongly counter-cyclical for those who lost their job in the previous year, with a correlation with the unemployment rate of 0.44 (March CPS: 0.60). The magnitude is smaller as a percentage-point increase in the unemployment rate leads to a 0.75 percent increase (March CPS: 0.95 percent) in the average residual wage of the unemployed, as compared to a 2.77 percent increase (March CPS: 2.59 percent) 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 de-trended series of each component of the predicted wage for those currently unemployed on the de-trended 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 CPS ORG sample and the March CPS sample. This demonstrates that attrition

is not causing any major bias in my estimates, as the March CPS contains backward looking information on wages and thus does not rely on matching individuals across survey waves.

One drawback of the analysis with the data from the CPS ORG sample is that it restricts the sample to those who were employed 12 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 unemployed in the monthly CPS sample, which is fully representative of the population of unemployed workers and does not face issues related to attrition. The results in row 3 of Table 1 are very similar to the results in the other 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 compositional changes in the pool of unemployed over the business cycle.

One way to assess the magnitude of the compositional shifts is to compare them to typical movements in the aggregate labor productivity. A one-standard deviation increase in the de-trended 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, whereas the standard deviation of the de-trended aggregate labor productivity is 2 log points for the United States (Shimer 2005). 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 US business cycle. I also computed the cyclicality of the predicted wage for the *employed* with the monthly CPS files and found a coefficient of 0.14 compared to a coefficient of 1.84 for the predicted wage of the unemployed (see row 3 in Table 1), showing that the composition of both pools moves in the same direction, but the compositional shifts are an order of magnitude larger for the unemployed.[12]

One thing to keep in mind is that the reported series are HP-filtered such that the mean is zero for both the employed and unemployed. The mean of the unfiltered series is, however, considerably lower for the unemployed, suggesting that they are on average of lower quality but become more similar to the employed in recessions.[13]

A potential limitation of the analysis of compositional changes in terms of the previous 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). 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. The results reported in online Appendix Table C.6 show that the compositional changes in the pool of unemployed in terms of the residual wage

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[12] See online Appendix B.1 for further evidence on the compositional changes among the employed.
[13] See Figure 3 in online Appendix C, which shows the distribution of unemployed workers by wage decile.

are not affected at all by controlling for employer size in the wage regression. This may seem in contradiction with Moscarini and Postel-Vinay (2012) who document 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 are driven by hirings rather than separations, in which case we would not expect to see any changes in the composition in the pool of unemployed in terms of the size of the *previous* employer. Consistent with this hypothesis, in a more recent paper Moscarini and Postel-Vinay (2016) show that over the course of the Great Recessions hire rates dropped sharply at larger establishments relative to hire rates at smaller establishments.

Table 1 provides evidence on the compositional changes in the pool of unemployed in the NLSY79. 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.[14] 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 toward 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 online Appendix Table C.10, the results are very similar when I include in the sample only individuals who changed jobs five times or more over the sample period. Overall, the estimates in the NLSY79 provide evidence that the compositional effects in terms of the residual wage are not driven by transitory effects.[15]

C. *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

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[14] The coefficient on the raw wage is somewhat lower than in the CPS data, because the NLSY79 follows a cohort of individuals similar in age and, to some extent, also in educational attainment.

[15] These results are also consistent 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 noncognitive test scores from military enlistment for the years 1991 to 2011. We construct a skill index by relating these cognitive and noncognitive 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 noncognitive skills.

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 four each year, and the transitions are analyzed for subsequent interviews (i.e., monthly transitions between interviews five, six, seven, and eight).

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 margin is more important for the changes in the composition of the unemployed and thus I run the following regressions:

$$(6) \qquad \ln x_{it} = \alpha_i^x + \beta_i^x \ln U_t + \varepsilon_{it}^x,$$

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 percent increase in the aggregate unemployment rate (the coefficient β_i^x). All series are monthly, seasonally adjusted, and HP-filtered with smoothing parameter 900,000.[16]

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 more than twice as large for individuals with high wages compared to those below the median. The difference is somewhat smaller when looking at the cyclicality of separations for those below and above the median residual wage: the ratio of $\frac{\beta_{low}^{sep}}{\beta_{high}^{sep}}$ is 0.70 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, the ratio of the cyclicality of separations between the low- and high-wage group is 0.54, 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 higher for those above the median wage, but the pattern reverses for the residuals and the differences are not statistically significant. Overall, I thus conclude that

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[16] I follow Bils, Chang, and Kim (2009) who HP-filter the monthly time series with a smoothing parameter of 900,000, which is equivalent to Shimer's (2005) smoothing parameter of 100,000 for quarterly data. The published version of Bils, Chang, and Kim no longer follows this de-trending choice. Online Appendix Tables C.2 and C.3 show that my results are robust to HP-filtering with a smoothing parameter of 14,400.

Table 2—The Cyclicality of Separation, Job Finding, and Unemployment Rates, by Wage Group (*Below and Above Median*)

		A. Based on hourly wage		B. Based on Mincer residual	
		Low	High	Low	High
Separation rates	Average	0.014	0.007	0.012	0.009
	Cyclicality	0.32	0.74	0.42	0.60
		(0.09)	(0.09)	(0.07)	(0.08)
Job finding rates	Average	0.32	0.31	0.31	0.32
	Cyclicality	−0.55	−0.62	−0.63	−0.54
		(0.05)	(0.07)	(0.06)	(0.07)
Unemployment rates	Average	0.045	0.024	0.038	0.028
	Cyclicality	0.79	1.31	0.91	1.11
		(0.03)	(0.04)	(0.02)	(0.03)

Notes: Newey-West corrected standard errors in parentheses. All series are HP-filtered with a smoothing parameter of 900,000. The cyclicality is measured as the coefficient β 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. The sample unemployment rate is instrumented with the official unemployment rate to address 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.

changes in the composition of the pool in terms of the previous wage are driven almost entirely by the different cyclicality of separations across wage groups and not by differences in the cyclicality of job findings.[17]

The facts documented in this paper are robust across a large range of different specifications and sample selection criteria (see online Appendix Tables C.1, C.2, and C.3). Online Appendix Table C.4 shows the cyclicality of transitions from unemployment to out of the labor force, which is similar for low- and high-wage workers. This suggests that discouragement cannot account for the compositional shifts in the pool of unemployed. Online Appendix Table C.4 also reports the cyclicality of job-to-job flows by wage group. This evidence does not support the view that the high cyclicality of separations for high-wage workers is driven by the fact that direct job-to-job transitions decrease strongly during recessions for this group. On the contrary, high-wage workers appear to have less cyclical job-to-job transitions than low-wage workers. Online Appendix Table C.5 splits the CPS ORG sample by quartiles of the wage distribution each year and finds that separations are most cyclical in the highest quartile. Online Appendix Table C.7 provides evidence that the compositional shifts are explained mostly by compositional changes within types of unemployed rather than shifts between job losers, job leavers, and re- and new entrants. Finally, online Appendix Table C.11 shows that, in the NLSY79 data, separations are more cyclical for high-wage workers whereas the cyclicality of job finding rates is similar across wage groups. These results hold even when dividing the sample into those with low and high individual fixed effects.

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[17] My results are consistent with Fujita and Ramey (2009) who show that separations account for about 50 percent of the volatility of unemployment. Using equation (4), I find that separations account for 37 percent of the volatility of unemployment for the low-wage group and for 54 percent for the high-wage group.

IV. Theory

In this section, I evaluate a number of theories that can potentially explain the compositional shifts in the pool of unemployed over the US business cycle. A key feature of these theories relates to the source of heterogeneity that generates differences in pre-displacement wages. I start by evaluating standard theories of wage setting and unemployment, where unemployed workers are homogeneous and differ in their pre-displacement wages only due to ex post heterogeneity, i.e., heterogeneity that arises after a match is formed. I then proceed with assessing models that allow for ex ante differences in worker heterogeneity in productivity and other parameters. The key goal of the theoretical exercise is to evaluate whether these models fit the main facts documented in the paper, which are, first and foremost, the large counter-cyclicality of the average pre-displacement wage, second, the higher cyclicality of separations for high-wage workers and, third, the equal cyclicality of job finding rates across groups. Note that, while models with ex post heterogeneity necessarily fit the third fact, as workers do not differ prior to matching to a firm, models with ex ante worker heterogeneity may generate counterfactual differences in the cyclicality of job finding rates across groups.

A. *Models with Ex Post Heterogeneity in Productivity and Wages*

I start by evaluating a standard search-matching model with match-specific productivity and endogenous separations. The main reference is Pissarides (2000), which I follow for the most part and thus defer the details to online Appendix D. There is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function $M = \kappa u^{\eta} v^{1-\eta}$, where u is the mass of unemployed, v the mass of vacant firms, κ is matching efficiency, and labor market tightness is $\theta = \frac{v}{u}$. Match productivity is defined as zx where z is aggregate productivity and x match-specific productivity. The aggregate state in this benchmark model is $Z = z$, but will include additional variables further below. The unemployed worker receives flow-value of unemployment b and vacant firms pay vacancy posting cost c. Wages are assumed to satisfy the standard Nash-bargaining solution and separations occur whenever the joint match surplus, $S(Z, x)$, 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 $S(Z, R(Z)) = 0$.

I calibrate the parameters in the model to the standard values in the literature as shown in Table 3. The period length of the model is one month and the discount factor β is set to match an annualized interest rate of 4.17 percent. The elasticity of the matching function η is in accordance with estimates from micro studies and is set to 0.5. The matching efficiency κ is a free parameter in the model and chosen such that $\theta = 1$ on average. The worker's bargaining power is set equal to the elasticity of the matching function in order to satisfy the Hosios condition. The flow value of unemployment b is set to 0.71 as in Hall and Milgrom (2008). 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

TABLE 3—BASELINE PARAMETER VALUES

Parameter/value	Description	Parameter/value	Description
$\beta = 0.9966$	Discount factor	$z_b = 0.98$, $z_g = 1.02$	Aggr. productivity in bad and good state
$\kappa = 0.31$	Matching efficiency	$\pi_{gb} = \pi_{bg} = 1/24$	Transition probabilities for aggr. shocks
$\eta = 0.5$	Elasticity of matching function	$\ln(x') = 0.98 \ln(x) + \varepsilon$	Process for match-specific productivity x
$\alpha = 0.5$	Worker's bargaining share	$\sigma_\varepsilon = 0.021$	Std. of match-specific shocks ε
$b = 0.71$	Flow value of unemployment	$c = 0.28$	Vacancy-posting cost

Note: σ_ε and c are internally calibrated and vary across alternative model calibrations.

TABLE 4—COMPARISON OF STATISTICS FROM DATA AND SIMULATIONS OF DIFFERENT MODELS

	Cyclicality of pre-displacement wage	Cyclicality of separations		Cyclicality of job findings	
		w_{low}	w_{high}	w_{low}	w_{high}
Panel A. Data (matched CPS ORG sample)	2.77	0.32	0.74	−0.55	−0.62
Panel B. Models with ex post heterogeneity only					
1. Baseline model	0.08	0.74	1.06	−0.43	−0.43
2. Model with wage rigidity	0.05	0.96	1.17	−0.13	−0.13
3. Model with compensating differentials	−0.01	0.68	0.28	−0.60	−0.60
4. Model with cyclical productivity dispersion	0.31	0.73	1.80	−0.23	−0.23
Panel C. Models with ex ante and ex post heterogeneity					
1. Baseline model	−2.12	0.78	0.61	−0.55	−0.26
2. Model with firm and establishment death	−0.20	0.78	0.88	−0.36	−0.16
3. Model with heterogeneity in b only	0.19	0.55	0.82	−0.26	−0.55
4. Model with heterogeneity in σ_ε	4.24	0.56	1.25	−0.39	−0.42
5. Model with cyclical credit constraints	4.13	0.61	1.51	−0.35	−0.16

Notes: The average pre-displacement wage in the model simulations is measured the same way as in the empirical analysis (i.e., the average log wage from one year ago for those currently unemployed). All time series in the model simulations are HP-filtered.

of recessions and expansions of two years. The log of match-specific productivity is assumed to follow an AR(1) process with an autocorrelation coefficient of 0.98 as in Bils, Chang, and Kim (2012). The standard deviation of innovations, σ_ε, is set to match the average separation rate in the CPS ORG data (0.011) and the vacancy posting cost is set to match the average job finding rate in the CPS ORG data (0.31).

Table 4 shows the results of the simulations of the model, which produces a counter-cyclical pre-displacement wage. The reason is that workers with a high draw of match-specific productivity x in the past become more likely to separate in recessions when the reservation match-productivity threshold increases. However, the magnitude of these compositional shifts is tiny, with a cyclicality of the pre-displacement wage of 0.08 compared to 2.77 for the raw wage or 0.75 for the residual wage in the CPS ORG data. The main reasons are that, first, the 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.[18] Second, separations are only somewhat less cyclical for low-wage workers relative to separations for high-wage workers with a ratio of 0.70 compared to 0.43 in the data. As shown in online Appendix D, these results are very robust to alternative parameterizations of the model.

Model with Wage Rigidity.—Another explanation for the documented shifts toward high-wage workers in recessions may be that wage rigidity leads firms to fire workers with inefficiently high wages. To assess this formally, I introduce wage rigidity into the model above by assuming that wages are Nash-bargained in a staggered fashion as in Gertler and Trigari (2009). Once the match is formed, wages are renegotiated according to the Nash-bargaining rule with probability τ. Separations, therefore, may be inefficient in cases where the wage cannot be reset and either match-specific productivity x or aggregate productivity z changes. I set the value of τ to 0.0575 to match the lower end of the range of the quarterly frequency of wage adjustments reported by Barattieri, Basu, and Gottschalk (2014). The results in Table 4 show that wage rigidity has a very modest impact on the cyclicality of the pre-displacement wage. In fact, the cyclicality of the pre-displacement wage is even lower than for the baseline model without wage rigidity, which is due to the fact that in the model with wage rigidity match-specific shocks tend to produce inefficient separations among high-wage workers even in good times, which further limits the cyclicality of separations for high-wage workers. Online Appendix E discusses the details of the model and various robustness checks.

Compensating Differentials for Unemployment Risk.—One may argue that wages compensate for the risk of layoff and thus in recessions the pool of unemployed shifts toward workers who held high-wage jobs prior to displacement. To assess this formally, online Appendix F sets up a simple model of risk averse workers in a frictional labor market. There are two types of jobs, which differ in their separation risk, which is calibrated to the average and cyclicality of separations below and above the median wage in the CPS data. Table 4, however, shows that the model generates compositional shifts in the opposite direction of the data. The reason is that the *average* separation risk dominates the cyclical separation risk in terms of the wage premium and thus the model predicts a counterfactually higher wage for the group with a high average separation rate. Moreover, what matters for compensating differentials is not the cyclicality in the log but rather the cyclicality in the level of separations, which differs only slightly between the low- and high-wage group in the data.

Model with Cyclical Productivity Dispersion.—Another source of separations in recessions may be due to counter-cyclical dispersion in firm productivity, as in the models of Bloom (2009) and Christiano, Motto, and Rostagno (2014). If the variance of shocks to firm-level productivity increases in recessions, even highly productive matches may be at risk of separation and thus this may disproportionally

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[18] See Hornstein, Krusell, and Violante (2011) for an elaborate analysis of wage dispersion in search models.

affect separations of workers further up in the wage distribution. To assess this formally, I assume that the standard deviation of match-specific shocks in the benchmark model above is counter-cyclical and increases by 10 percent in recessions, consistent with the evidence in Kehrig (2015). Table 4 shows that this model has some promise in explaining at least part of the patterns, with a cyclicality of the pre-displacement wage of 0.31. This is still far below the cyclicality of 2.77 for the raw wage but closer to the 0.75 for the residual wage. Moreover, Kehrig shows that the cross-sectional productivity dispersion spiked up sharply in the Great Recession, but as Figure 3 shows, the compositional shifts were not unusually strong over that period.

B. *Models with Ex Ante Worker Heterogeneity*

In this section, I extend the model with match-specific productivity and endogenous separations from the previous section to the case of heterogeneity in worker types (indexed by i) who potentially differ in their market productivity a_i and other parameters. This extension naturally produces more dispersion in pre-displacement wages. It is also motivated by the fact that the shifts documented in the CPS data can be attributed to a large extent to observable worker characteristics and are not driven by firm-size effects, and additional evidence from the NLSY79 that the compositional changes are associated with permanent worker effects rather than transitory effects in pre-displacement wages.

Match productivity is defined as zxa_i where z is aggregate productivity and x match-specific productivity as before. Following Bils, Chang, and Kim (2012), firms can direct their search to a particular worker type and thus labor markets are segmented. There is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function, $M_i = \kappa_i u_i^\eta v_i^{1-\eta}$. See online Appendix G for further details.

The calibration of the model follows the calibration of the model in the previous section unless otherwise stated here. The key challenge in the calibration of the model is how to set values of parameters that potentially depend on worker type i. I set $a_{low} = 0.575$ and $a_{high} = 1.425$ to match the differences in average wages for workers below and above the median wage in a given year in the CPS ORG sample. The standard deviation of match-specific shocks, σ_ε, is set to match an average flow value of unemployment of 0.71 as in Hall and Milgrom (2008), which implies a value of $\sigma_\varepsilon = 0.028$. To impose discipline on the calibration, the group-specific flow-values of unemployment b_i and vacancy posting costs c_i are set to match the group-specific average separation and job finding rates in the CPS ORG data. This calibration strategy results in a lower flow-value of unemployment relative to productivity for high-ability workers, which is consistent with the fact that most unemployment insurance systems replace previous earnings only up to a maximum benefit amount. Moreover, b_i captures the utility derived from additional leisure and home production during unemployment, which is likely to be less than proportional to market ability, a_i.

Table 4 reports the results for the simulations of this baseline model with ex ante differences in worker productivity. The model, however, does poorly in capturing the documented facts, as it generates a large *pro*-cyclical pre-displacement wage

and, a higher, not lower, cyclicality of separations for the low-ability types. The intuition for this failure is related to the cyclical behavior of the worker's outside option, which increases less than proportionally with aggregate productivity because b_i is constant over the cycle and thus generates counter-cyclical separations. This is the case even more so for low-ability workers as the flow-value of unemployment is higher relative to their productivity and thus accounts for a larger share of the total value of unemployment. Online Appendix Table G.1 shows that the pre-displacement wage remains pro-cyclical for various parameterizations of the model.

Model with Firm and Establishment Death.—The shifts toward high-wage workers may also be driven by the death of firms and establishments in recessions. If workers of different ability are randomly distributed across firms and establishments, then firm and establishment death will increase separations for workers of all types by the same absolute number, and more in percentage terms for those with low average separation rates (i.e., high-ability workers). A simple way of modeling such shocks is to introduce an exogenous separation shock λ, which affects all matches independently of productivity x and type i. Consistent with the Business Dynamics Statistics (BDS) from the Census, I set the monthly rate of firm death λ to 0.49 percent in recessions and to 0.41 percent in expansions (see online Appendix Table G.6 for details). The results in Table 4 show that firm death improves the quantitative performance of the model relative to the baseline model, but it still predicts a slightly pro-cyclical pre-displacement wage. The failure of the model depends on the amplification of aggregate productivity shocks, as a calibration with a lower average flow value of unemployment (see panel B.2 in online Appendix Table G.2), and thus less amplification yields a cyclicality of 0.87. This, however, is still well below the cyclicality of 2.77 in the data. Moreover, the average flow value of unemployment in this calibration is 0.24, which is clearly below the values typically used in the literature, and thus I conclude that firm and establishment death is not cyclical enough to account for the patterns in the data on its own.[19]

Model with Heterogeneity in b Only.—The empirical results may also be driven by a higher cyclicality of separations for workers with higher flow-values of unemployment b_i in a model where workers do not differ in market productivity ($a_{low} = a_{high}$). In such a model, high-b workers are paid higher wages due to the higher value of their outside option. As above, I set the flow value of unemployment b_i to match the average separation rate for each group in the data but let the model decide which is the high-wage group. While this model predicts more cyclical separations for high-wage workers, as shown in Table 4, the magnitude of the compositional shifts is small. Moreover, in sharp contradiction to the evidence in Table 2, the model results in a higher *average* separation rate for high-wage workers.

Model with Heterogeneity in σ_ε.—Table 4 shows the results for an alternative calibration strategy of the model with heterogeneous workers where flow-values of unemployment are assumed to be proportional to worker productivity ($b_i = ba_i$)

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[19]Online Appendix D.2 shows that this conclusion carries over to the model with ex post heterogeneity.

and instead the variance of match-specific productivity shocks is set to match the average separation rates *for each group*, which results in $\sigma_{\varepsilon, low} = 0.037$ and $\sigma_{\varepsilon, high} = 0.016$.[20] The flow-value of unemployment b is set to 0.71 as in Hall and Milgrom (2008). 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. The reason for the higher cyclicality of separations is that a lower variance of match-specific productivity shocks increases the density of matches at the separation threshold and thus changes in the threshold generate larger responses for these workers. Interestingly, this model also matches the fact that the average and cyclicality of job findings tend to be very similar across wage groups, which is a challenge for models with ex ante worker heterogeneity. The reason is that, in contrast to other calibrations of the model with worker heterogeneity, this calibration preserves the proportionality of flow values of unemployment to worker-level productivity and thus aggregate productivity shocks raise the values of jobs in proportion to the productivity of the worker being hired. Online Appendix Table G.2 shows that these results are robust to various parameterizations of the model.

Model with Credit-Constraint Shocks.—Another explanation for the shifts toward high-wage workers in recessions may be related to the fact that recessions are often periods where access to credit becomes more difficult.[21] If firms face temporary shortfalls in productivity, then a tightening of credit may force firms to fire some of their workers even though it would be profitable in the long run to not do so. To more formally evaluate this possibility, I incorporate shocks to credit-constraints into my benchmark model with ex ante heterogeneous workers. I use a shortcut by assuming that in recessions, worker-firm matches face a constraint to produce cash flows above some number $-\gamma$:

$$(7) \qquad\qquad zxa_i - w_i(Z, x) \geq -\gamma.$$

Workers may be willing to take a wage cut in order to remain employed, and thus, I assume that wages satisfy the Nash-bargaining solution $w_i^{NB}(Z, x)$ as long as the cash-flow constraint (7) is met, but otherwise adjust to meet the constraint.[22] If the cash-flow constraint cannot be met at any acceptable wage for the worker, worker-firm matches will dissolve.

I use the same parameter values as for the baseline calibration above, and set γ to 0.08 in recessions and assume it to be nonbinding in expansions.[23] 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 online Appendix Table H, the model produces a counter-cyclical pre-displacement wage

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[20] This calibration strategy is similar to the one in Bils, Chang, and Kim (2012).

[21] Kiyotaki and Moore (1997) provide a theoretical rationale for cyclical variations in borrowing constraints.

[22] The model thus allows for back-loading of wage profiles as in Michelacci and Quadrini (2009) and Guiso, Pistaferri, and Schivardi (2013). See online Appendix H for details.

[23] One may argue that these constraints are very tight as firms need less than one year of average cash flows (about 1 percent of average labor productivity) to repay current losses. Note, however, that in the model, match-specific productivity is highly serially correlated and thus it takes far longer to recover current losses.

for various calibrations of the size of the shock. The important intuition for the result is that in the baseline model *without* cash-flow constraints, firms are willing to pay workers above their current productivity when faced with a temporary shortfall in productivity (either due to x or z) as they expect to make up for current losses in the future. This is particularly true for high-ability workers, who are expected to produce more sizable profits once productivity recovers, and thus a tightening of credit constraints affects separations of these workers first and most strongly.

A potential issue with the model may be that firms are small in the sense that they only have one employee. One may argue that firms with multiple employees would lay off low-ability rather than high-ability workers in the face of binding credit constraints. Notice, however, that due to the imperfect indexation of flow values of unemployment b to worker ability a in the model, high-ability workers separate at lower values of match-specific productivity x and it takes longer for these marginal matches to recover current losses. Therefore, it should be optimal for a constrained firm to fire marginal high-ability workers rather than marginal low-ability workers and, thus, the main mechanism in my model should also be operative in a multi-worker firm setup. Of course, ideally, one should set up a multi-worker firm model to quantify the compositional effects arising from cash-flow constraints, but such a model is very complex and thus this important work is left for future research.[24]

Further Discussion.—The model with differences in the variance of match-specific shocks stands out in matching all the relevant facts in the paper. It is not entirely clear, however, why the variance of match-specific productivity shocks should be lower for high-ability workers. It is possible that high-ability workers face smaller shocks, if these shocks are of the learning type as in Jovanovic (1979) and high-ability workers are better able to identify suitable matches so that ex post there remains less to learn about the quality of the match. One way of evaluating this in the data is to look at the variance of wage changes, as the model predicts the variance of wage changes to be twice as high for the low-ability group. As shown in online Appendix Table G.5, in the CPS and the NLSY79, the variance of log wage changes is the same across wage groups. One issue with this exercise, however, is that measurement error in surveyed wages may be too large to draw meaningful inferences from this comparison.[25] A natural way forward thus would be to look at the variance of wage changes by wage group in administrative data, which is less riddled with measurement error.

The model with cyclical cash-flow constraints also is a promising explanation, as it matches the strong counter-cyclicality of the pre-displacement wage in the data. It counterfactually predicts that job finding rates are less pro-cyclical for high-ability workers. This, however, is in part due to the assumption that firms can direct their search toward a particular worker type. An alternative model where firms cannot direct their search generates an equal cyclicality of job finding across groups, as

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[24] See online Appendix H.4 for further details and simulation results. Stole and Zwiebel's (1996) intra-firm bargaining game would be a good starting point to modeling firm-level cash-flow constraints in a multi-worker firm setup. This, however, is very complex due to the interactions between the wage bargaining and the firm-level cash-flow constraint as well as the presence of low- and high-ability workers.

[25] The comparison of variances of log wage innovations may be further complicated in an environment with long-term contracting, where match-specific shocks do not necessarily translate into wage changes.

upon matching even low-ability workers produce a positive surplus and thus firms will hire them (see online Appendix I.2).

One may also wonder whether the theory based on cyclical credit constraints is consistent with the magnitude of the compositional shifts for each of the recessions covered in the empirical analysis. Figure 3 shows that the shift was not unusually strong during the Great Recession and was even somewhat weaker in terms of the residualized pre-displacement wage, 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.[26] 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 shock (see online Appendix Table H). 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 with time-series data on firm-level financial constraints is challenging.[27] A more promising avenue would be to use the approach of 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. One could 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 within-firm wage rankings prior to the credit shock. A firm-level analysis also allows for a test of the hump-shaped relationship between credit shocks and their compositional effects.

V. Conclusion

This paper provides a new fact about the composition of the unemployment pool over the US business cycle. In recessions, the pool of unemployed shifts toward 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 paper evaluates a number of theories that can potentially explain these patterns in the data. It finds that standard theories of wage setting and unemployment based on ex post heterogeneity have difficulty in explaining the documented facts. Furthermore, the paper assesses a search-matching model with endogenous separations and heterogeneous workers, and finds that a version of the model where

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[26] For example, Gilchrist and Zakrajšek (2012) construct an excess bond premium, which sharply increased in 2007–2008 and to a lesser degree in other recessions, except the one in 1990–1991, 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 Zakrajšek 2012).

[27] For the same reason, it is 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 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.

high-ability workers face a lower variance of shocks to match productivity is successful in explaining the compositional shifts in the data. Finally, a model with cyclical credit constraints also generates shifts toward high-ability workers in recessions, though it is difficult to reconcile this theory with shifts toward high-wage workers in recessions that did not show any signs of credit tightening.

The findings have important implications for models of aggregate fluctuations of the labor market, as shifts toward high-ability workers in recessions aggravate the lack of an amplification mechanism in the standard search-matching model. The documented facts may also explain the findings in Modestino, Shoag, and Ballance (2016) and Hershbein and Kahn (2016) who document that in recessions firms post vacancies with higher skill requirements, if firms respond to the changing composition of unemployment. Finally, the findings suggest that the welfare 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, shifts toward high-ability workers should attenuate the need for counter-cyclical unemployment insurance.[28]

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 makes it possible to refine the analysis in the NLSY79 data by separately identifying firm and worker fixed effects. Moreover, it allows us to determine directly the importance of establishment death for separations. 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 is obtained.

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[28] See, e.g., Schmieder, von Wachter, and Bender (2012).

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