ONLINE APPENDIXES for paper "Separations, Sorting and Cyclical Unemployment" by Andreas I. Mueller

The appendixes may repeat some text from the body of the paper for clarity.

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Appendix A. Data Sources

A.1 Matched CPS Outgoing Rotation Group (ORG) sample

I use the CPS ORG files for the years 1979 to 2012 provided by the Unicon Research Corporation, and follow Lemieux (2006) in the sample selection and the construction of the hourly wage series. More specifically, as in Lemieux (2006), I define the hourly wage as the usual weekly earnings divided by usual hours worked last week for non-hourly workers. Starting with the CPS redesign in 1994, workers with varying hours are not asked to report the usual weekly hours. I impute usual hours for these workers by running four separate regressions by gender and full-time/part-time status of usual hours on age, age squared, and dummies for race, ethnicity, educational attainment, marital status, and citizenship. I also construct an alternative hourly wage series, following Autor, Katz and Kearney (2008), where I divide usual weekly earnings with hours worked last week, and the results are robust to this modification.

Following Lemieux (2006), I exclude all observations with allocated earnings except where allocation flags are not available (January 1994 to August 1995). For the years 1989 to 1993, I use the unedited earnings variable to identify unallocated earnings, as only about 25% of allocated earnings were flagged as such (see also Hirsch and Schumacher, 2004). I also multiply top-coded weekly earnings by a factor 1.4 (the top codes are \$999 for 1979-1985, \$1,999 for 1986-1988, \$1,923 for 1989-1997, \$2,884.61 for 1998-2012) and use the unedited earnings variable for the years 1986-1988, as it has a higher top-code (\$1,999) than the edited earnings variable. I also follow Lemieux (2006) in the construction of the survey weights and multiply the earnings weights times hours worked last week. Finally, I adjust the hourly wage for inflation by dividing by the implicit price deflator for personal consumption expenditures and remove observations with hourly wage values less than \$1 or more than \$100 in 1979 dollars. As Lemieux, I restrict my sample to workers 16 to 64 with positive potential experience (age – years of education – 6). In addition, and specific to my analysis, I limit the sample to private sector employees who are not self-employed and not self-incorporated.

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 interviews 9, 10, 11 and 12 months later: 28.9% of the individuals in my sample had no match in interviews 5-8. Similarly to Bleakley, Ferris and Fuhrer (1999), I adjust the survey weights to account for attrition. More precisely, I run a logit regression of the likelihood of remaining in the sample for interviews 5 to 8 on observable characteristics (such as sex, age, education, race and marital status) for each year and multiply the existing survey weight with the inverse of the predicted value of the logit regression. This deflates the weight for groups and years with low attrition rates.[1] The total sample size is 1,203,455

[1] Abowd and Zellner (1985) propose a procedure of reweighing the data that minimizes the difference between

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 1,203,543 individuals, 79,463 experienced at least one month of unemployment in interview months 5-8.

A.2 March CPS sample

I use the CPS March supplement files for the years 1962 to 2012 provided by the Unicon Research Corporation, and follow Lemieux (2006) as well as Autor, Katz and Kearney (2008) in the sample selection and the construction of the wage series. I follow Lemieux (2006) and define the hourly wage as the wage and salary income over the previous calendar year divided by the product of weeks worked and usual weekly hours. For the years 1962 to 1975, weeks worked is only available as a categorical variable and it is not possible to follow Lemieux who does not include data from this period in his analysis. I use the weeks worked imputed by Unicon by the midpoint of each interval from data for the period 1976 and onwards (the intervals are 1-13 weeks, 14-26 weeks, 27-39 weeks, 40-47 weeks, 48-49 weeks and 50-52 weeks). Moreover, usual weekly hours for the previous calendar year are not available over this same period, and, therefore, I impute usual hours by running four separate regressions by gender and full-time/part-time status of usual hours on age, age squared and dummies for educational attainment, race and marital status for the years 1976 to 1978 and use the predicted value for this regression to impute hours in the years 1962 to 1975.[2] Autor, Katz and Kearney (2008) impute hours based on a regression including hours worked last week. While their procedure works well in general, the imputed hours worked last year are likely to greatly underestimate the actual hours worked last year for those currently unemployed, as by definition those currently unemployed did not work at all last week. As the hourly wage last year for those currently unemployed is the main focus of this paper, I decided to use the alternative approach using only demographics and full-time/part-time status last year for the imputations of hours worked last year.

Following Lemieux (2006), I exclude allocated earnings, except where allocation flags are not available (1962-1966), and multiply top-coded earnings times 1.4. The top codes in the March CPS data are $90,000 for the years 1962 to 1964, $99,900 for the years 1965 to 1967, $50,000 for the years 1968 to 1981 and $75,000 for the years 1985 to 1988. In 1989, the March CPS started to collect data on wage and salary income for both main and second jobs with separate top codes for each of these variables. The top code for the main job was $99,999 for the years 1989 to 1995, $150,000 for the years 1996 to 2002, $200,000 for the years 2003 to 2010 and $250,000 for

the stocks implied by the matched 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.

[2] Note that, for the year 1963, no information on educational attainment was available, so I only used information on age, race, and marital status for the imputations by gender and full-time/part-time status last year.

the years 2011 and 2012, whereas the top code for earnings from the second job changed more frequently and was $95,000 in 1989, $99,999 in 1990, $90,000 in 1991, $99,999 for the years 1992 to 1995, $25,000 for the years 1996 to 2002, $35,000 for the years 2003 to 2010, $47,000 in 2011 and $50,000 in 2012. Moreover, for the period 1996 and later, the March CPS wage and salary variable contains mean earnings above the top code for top coded observations. To maintain consistency across the years, I follow Lemieux (2006) and compute wage and salary earnings as the sum of the main job earnings and second job earnings with imputed earnings above the top-code and censor the sum at the top code of the main job ($99,999 for the years 1989 to 1995, $150,000 for the years 1996 to 2002, $200,000 for the years 2003 to 2010 and $250,000 in 2011 and 2012).[3] I also exclude observations where self-employment income is more than 10 percent of the wage and salary income, as usual hours last year also include self-employed hours for those who have income from self-employment besides their main job. Finally, I adjust the hourly wage for inflation by dividing by the implicit price deflator for personal consumption expenditures and remove observations with hourly wage values less than $1 or more than $100 in 1979 dollars. As Lemieux, I limit the analysis to workers 16 to 64 with positive potential experience (age last year – years of education – 6).

A.3 Monthly CPS sample

I use all data from the basic monthly CPS surveys for the years 1978 to 2012.[4] 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 34,472,816 observations out of which 1,625,525 were unemployed at the time of the survey.

A.4 NLSY79

I use data from the National Longitudinal Survey of Youth 1979 (NLSY79) for the years 1979-2012 to extend the main analysis with longitudinal data on wages and labor force status. I

[3] Lemieux's analysis only extends to 2003 and he uses a top code of $150,000 for the year 2003. The adjustment of the top code variable to $200,000 for the years 2003 to 2010 and to $250,000 for the years 2011 and 2012 takes into account the changes in the top code for earnings on the main job in these years.

[4] In some cases, I restrict the sample to the years 1980-2012, to be comparable to the CPS ORG sample.

construct the wage variable in the NLSY79 by using information on all jobs reported in the prior year. More precisely, I divide the total wage earnings in the prior year by total hours worked in the prior year. This measure is the same as the one used in the March CPS files. From 1982 to 2002, the total wage income last year was top-coded for the top two percent of the sample (with the group average of those in the top two percent). I adjust the wage income in other years, by replacing the wage income in the top two percent by the group average, to be consistent across all survey years. To be consistent with my analysis with the matched CPS ORG and the March CPS sample, I adjust the hourly wage for inflation by dividing by the implicit price deflator for personal consumption expenditures and remove observations with hourly wage values less than $1 or more than $100 in 1979 dollars. Furthermore, I restrict my sample to individuals of age 16 and older, exclude the military sample and use the custom weights available from the website (http://www.nlsinfo.org/weights/nlsy79), which create a longitudinal weight for every sample member who participated in at least one survey wave. I also restrict the sample to those with positive potential experience (age - years of education - 6) who are private sector employees and not self-employed nor self-incorporated. In addition, given that the longitudinal sample is biased towards younger workers, I exclude individuals who are currently enrolled in school from my analysis and only use observations for my analysis after entry into the labor market, which I define for each individual as the first survey year with valid wage data. The analysis is restricted to the years 1979-2011 as for the final year of the sample labor force status was only available up to date of the interview.This leaves a sample of 6,923 individuals and 193,467 yearly observations on labor force status of which 32,055 are recorded as unemployed at some point over the course of a year. To construct a measure of the composition of the pool of unemployed in the past calendar year, I thus compute the number of weeks unemployed in a given calendar year and divide by 52 and weigh all my indicators of the pool of unemployed by the fraction of the year unemployed (i.e., a person unemployed for the entire year will get a weight of 1, a person unemployed for 1 week a weight of 1/52). To assess whether this approach resulted in a reasonable measure of the unemployment rate, I correlate the sample unemployment rate (defined as the fraction of the year unemployed) with the official unemployment rate. For the unfiltered data, the correlation coefficient is 0.78 and for the HP-filtered data, the correlation coefficient is 0.87, which is high given that the sample from the NLSY79 gradually ages over the years, as it follows a representative cohort of young individuals in 1979, whereas the official unemployment rate is representative of the population each year.

Computing monthly transitions between employed and unemployed in the NLYS79. The NLSY79 keeps detailed record of the labor force status for each week between interviews. This is true even for the later period where interviews were held only at bi-annual frequency. To compute the transition rates between employment and unemployment in a comparable fashion to the CPS, I defined a reference week in each month of the sample period, which was the week including the 15th of the month. In a second step, I computed the average *monthly* transition rate between employment and unemployment (and vice versa) for each calendar year in the period 1979 to 2011. I did not compute the monthly transition rate for each month of the sample period, as for some sub-periods and sub-groups, there were only few observations in given cell.

A.5 Industry and occupation codes

At the 2-digit level, the NBER created industry codes that are consistent across all years. At the 3-digit level, the occupation and industry classification in the CPS ORG files changed coding schemes in 1983, 1992 and 2003. I use the variables occ1950 and ind1950 from the IPUMS-CPS, which is a harmonized 3-digit occupation and industry scheme across all years.

A.6 Mincerian wage regressions

In part of the analysis in Section 3, I use wage residuals from a regression of the log hourly wage on potential experience (quadratic polynomial), 11 dummies for educational attainment (dummies for 0, 1-4, 5-8, 9, 10 and 11 years of education, 12 years of education but no high school degree, high school degree, some college education, bachelor degree and graduate degree), gender, marital status, an interaction term between marital status and gender, dummies for black, Hispanic and other race and dummies for each state, year, occupation and industry. In order to take into account changes in the coefficients of the regression over time, for each year, I run the regression in a rolling window, including data from plus and minus five years, and then compute the residual for that year.[5] For the NLSY79, in general, I follow the same approach, except that the sample is too small to allow for rolling window regression. Instead, I run a regression for all years but interact all variables (including the industry and occupation dummies) with a quadratic polynomial of the time trend.

A.7 Summary statistics of different samples

Table A.1 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

[5]The reason for choosing a relatively wide window is to minimize the effect of imprecisely estimated coefficients (in particular, for the many state, industry and occupation effects). The main results in the paper, however, a very similar if one reduces the width of the window of the regression sample.

representative cohort of workers and thus not representative of the population every year. Over all years of the survey, the average characteristics of these workers are somewhat younger and less educated compared to the CPS.

TABLE A.1 DESCRIPTIVE STATISTICS OF DIFFERENT SAMPLES

	Matched CPS ORG sample		Monthly CPS		CPS march supplement		NLSY79	
	% of pop.	% of unempl.	% of pop.	% of unempl.	% of pop.	% of unempl.	% of pop.	% of unempl.
Female	41.7%	37.0%	50.9%	44.3%	39.6%	33.2%	49.4%	42.7%
Married	60.3%	47.7%	60.6%	43.1%	63.6%	49.8%	38.6%	27.5%
Age								
Age 16-19	4.1%	9.7%	6.7%	13.6%	1.7%	3.9%	3.6%	10.0%
Age 20-29	27.5%	34.3%	24.0%	34.4%	25.9%	34.7%	39.3%	49.1%
Age 30-39	28.9%	24.8%	24.1%	22.4%	26.9%	25.3%	30.7%	20.6%
Age 40-49	22.1%	17.7%	21.2%	16.0%	23.6%	19.1%	21.0%	15.0%
Age 50-59	14.1%	11.1%	17.0%	10.8%	17.2%	13.4%	5.3%	5.3%
Age 60-64	3.3%	2.5%	7.0%	2.8%	4.6%	3.4%	0.0%	0.0%
Education								
Less than high school	14.1%	24.8%	19.5%	30.3%	17.6%	27.8%	7.1%	15.2%
High school degree	36.6%	40.5%	33.4%	37.1%	36.3%	40.5%	34.2%	42.7%
Some college	26.2%	22.7%	24.7%	21.2%	24.2%	20.8%	14.7%	12.2%
College degree	23.2%	12.0%	22.4%	11.4%	21.9%	10.8%	43.9%	29.9%
Race/Ethnicity[1]								
White	75.9%	68.1%	73.0%	60.7%	77.3%	69.5%	80.7%	70.8%
Black	9.1%	13.4%	11.8%	21.1%	9.8%	14.9%	13.0%	21.7%
Hispanic	11.0%	14.8%	10.7%	13.8%	9.1%	12.2%	6.3%	7.5%
Other	4.1%	3.7%	4.5%	4.4%	3.8%	3.4%	--	--
Years	1980-2012		1980-2012		1962-2012		1979-2011	
N	1,203,543	79,463	34,472,816	1,625,525	2,637,523	140,320	193,467	32,055

[1] For the NLSY79, information for race and ethnicity only included black, hispanic and non-black/non-hispanic.

Appendix B. The relationship between the composition of the unemployed and the composition of the employed

Let's divide the pool of employed into two equally large group, i.e., into those below and above the median. The share of unemployed and the share of employed of group i then can be written as:

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

$$\phi_{it}^{E} = \phi_{it}^{L}\frac{E_{it}}{E_t} = \frac{\phi_{it}^{L}(1-U_{it})}{1-\phi_{it}^{L}U_{it} - (1-\phi_{it}^{L})U_{jt}} \quad (2)$$

$$\phi_{it}^{L} = \phi_i\frac{P_{it}}{P_t} \quad (3)$$

where ϕ_i^x is the share of group i in pool of $x = U$(nemployed), E(mployed), (In the)L(abor Force) and where j stands for the complement group of group i (i.e., including all individuals which are not included in group i). The changes in the shares in the pool of unemployed then can be written as

$$\begin{aligned}
d\phi_{it}^{U} &= \frac{\partial\phi_{it}^{U}}{\partial U_{it}}dU_{it} + \frac{\partial\phi_{it}^{U}}{\partial U_{jt}}dU_{jt} + \frac{\partial\phi_{it}^{U}}{\partial\phi_{it}^{L}}d\phi_{it}^{L} \\
&= \left[\frac{\phi_{it}^{L}\left(\phi_{it}^{L}U_{it} + (1-\phi_{it}^{L})U_{jt}\right) - \phi_{it}^{L}\phi_{it}^{L}U_{it}}{\left(\phi_{it}^{L}U_{it} + (1-\phi_{it}^{L})U_{jt}\right)^2}\right]dU_{it} \\
&\quad - \left[\frac{(1-\phi_{it}^{L})\phi_{it}^{L}U_{it}}{\left(\phi_{it}^{L}U_{it} + (1-\phi_{it}^{L})U_{jt}\right)^2}\right]dU_{jt} \\
&\quad + \left[\frac{U_{it}\left(\phi_{it}^{L}U_{it} + (1-\phi_{it}^{L})U_{jt}\right) - \phi_{it}^{L}U_{it}(U_{it} - U_{jt})}{\left(\phi_{it}^{L}U_{it} + (1-\phi_{it}^{L})U_{jt}\right)^2}\right]d\phi_{it}^{L} \\
&= \frac{\phi_{it}^{U}(1-\phi_{it}^{U})}{U_{it}}dU_{it} - \frac{\phi_{it}^{U}(1-\phi_{it}^{U})}{U_{jt}}dU_{jt} + \frac{\phi_{it}^{U}}{\phi_{it}^{L}}\frac{1-\phi_{it}^{U}}{1-\phi_{it}^{L}}d\phi_{it}^{L} \\
&= \phi_{it}^{U}\left(1-\phi_{it}^{U}\right)\left[d\ln U_{it} - d\ln U_{jt}\right] + \frac{\phi_{it}^{U}\left(1-\phi_{it}^{U}\right)}{\phi_{it}^{L}\left(1-\phi_{it}^{L}\right)}d\phi_{it}^{L}.
\end{aligned}$$

By analogy, changes in the share of employed can be written as

$$
\begin{aligned}
d\phi_{it}^{E} &= \phi_{it}^{E}\left(1-\phi_{it}^{E}\right)\left[d\ln E_{it}-d\ln E_{jt}\right]+\frac{\phi_{it}^{E}\left(1-\phi_{it}^{E}\right)}{\phi_{it}^{L}\left(1-\phi_{it}^{L}\right)}d\phi_{it}^{L} \\
&= \phi_{it}^{E}\left(1-\phi_{it}^{E}\right)\left[d\ln\left(1-U_{it}\right)-d\ln\left(1-U_{jt}\right)\right]+\frac{\phi_{it}^{E}\left(1-\phi_{it}^{E}\right)}{\phi_{it}^{L}\left(1-\phi_{it}^{L}\right)}d\phi_{it}^{L} \\
&= \phi_{it}^{E}\left(1-\phi_{it}^{E}\right)\left[\frac{U_{jt}}{1-U_{jt}}d\ln U_{jt}-\frac{U_{it}}{1-U_{it}}d\ln U_{it}\right]+\frac{\phi_{it}^{E}\left(1-\phi_{it}^{E}\right)}{\phi_{it}^{L}\left(1-\phi_{it}^{L}\right)}d\phi_{it}^{L} \\
&= -\phi_{it}^{E}\left(1-\phi_{it}^{U}\right)\frac{U_t}{E_t}\left[\frac{1-\phi_{it}^{E}}{1-\phi_{it}^{U}}\frac{\phi_{it}^{U}}{\phi_{it}^{E}}d\ln U_{it}-d\ln U_{jt}\right]+\frac{\phi_{it}^{E}\left(1-\phi_{it}^{E}\right)}{\phi_{it}^{L}\left(1-\phi_{it}^{L}\right)}d\phi_{it}^{L}
\end{aligned}
$$

Changes in the composition of the labor force can be written as

$$
d\phi_{it}^{L}=\phi_{it}^{L}d\ln\frac{P_{it}}{P_t}.
$$

Transforming these equations into elasticities, we get:

$$
\begin{aligned}
\frac{d\ln\phi_{it}^{U}}{d\ln U_t} &= \left(1-\phi_{it}^{U}\right)\left[\frac{d\ln U_{it}}{d\ln U_t}-\frac{d\ln U_{jt}}{d\ln U_t}\right]+\frac{1-\phi_{it}^{U}}{1-\phi_{it}^{L}}\left[\frac{d\ln P_{it}}{d\ln U_t}-\frac{d\ln P}{d\ln U_t}\right] \\
\frac{d\ln\phi_{it}^{E}}{d\ln U_t} &= \left(1-\phi_{it}^{E}\right)\left[\frac{U_{jt}}{1-U_{jt}}d\ln U_{jt}-\frac{U_{it}}{1-U_{it}}d\ln U_{it}\right]+\frac{1-\phi_{it}^{E}}{1-\phi_{it}^{L}}\left[\frac{d\ln P_{it}}{d\ln U_t}-\frac{d\ln P}{d\ln U_t}\right]
\end{aligned}
$$

If we abstract from movements in the composition of the labor force, then this can be evaluated with the results from Panel A in Table 2:

$$
\begin{aligned}
\frac{d\ln\phi_{high,t}^{U}}{d\ln U_t} &= \frac{0.045}{0.024+0.045}(1.31-0.79)=0.339 \\
\frac{d\ln\phi_{high,t}^{E}}{d\ln U_t} &= \frac{1-0.045}{2-0.024-0.045}\left(\frac{0.045}{1-0.045}0.79-\frac{0.024}{1-0.024}1.31\right)=0.002
\end{aligned}
$$

where we use the fact that $\phi_{high,t}^{L}=0.5$, $U_{low,t}=0.045$, $U_{high,t}=0.024$, $\frac{d\ln U_{low,t}}{d\ln U_t}=0.79$ and $\frac{d\ln U_{high,t}}{d\ln U_t}=1.31$ from Panel A and that $1-\phi_{it}^{U}=\phi_{jt}^{U}=\frac{\phi_{jt}^{L}U_{jt}}{\phi_{it}^{L}U_{it}+(1-\phi_{it}^{L})U_{jt}}$. This suggests that our estimates imply that the pool of employed sorts in the same direction as the pool of unemployed but on a much smaller scale. Keep in mind, 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, we would expect the movements in the pool of employed to be somewhat stronger (though still much smaller as for the pool of unemployed, as shown below). Moreover, compositional changes in the composition of the pool of the labor force will lead to changes in the pool of employed as well as unemployed in the same direction. As shown below, there are small changes in the pool of employed towards high-wage workers in periods of high unemployment.

B.1 Direct evidence on compositional changes in the pool of employed and the labor force

In this section, I provide some direct evidence on the compositional changes in the pool of employed. Figure 1 shows the ratios of employment rates similar to the figure of ratios of *un*employment rates in the paper, but on a much smaller scale. Table B.1 shows the cyclicality of the ratios of unemployment rates, employment rates and labor force participation rates. The cyclicality of the ratios of unemployment rates tends to be an order of magnitude larger compared to the cyclicality of the ratios of employment or labor force participation rates. The results are similar when the sample is restricted to month in sample (MIS) 2, which suffers from least attrition.

The larger magnitude of the shifts among unemployed compared to the employed is not a mechanical result that arises due to changes in the composition of the labor force. If separation and job finding rates are indiscriminate and constant across the two groups and thus the flow steady state unemployment rates are the same for the two groups, then on average the share of high-wage workers among the unemployed and employed is the same. Under these assumptions, changes in the composition of the pool of employed – such as due to changes in the composition of the labor force – translate into compositional changes in the pool of unemployed of the same magnitude, as one can deduce easily from the equations shown above (equations 2 and 3 in the paper). Moreover, in reality separations are not indiscriminate, but instead higher on average among the low-wage group, and one can show that for this reason the average share of high-wage workers is 35 percent among the unemployed and 50 percent among the employed.[6] Therefore, as one can deduce from the equations above (equations 2 and 3 in the paper) changes towards high-wage workers in the labor force, will translate into slightly larger shifts towards high-wage workers among the employed than the unemployed (i.e., $d\phi_{i,t}^{E} > d\phi_{i,t}^{U}$). I conclude that the much larger magnitude of the shifts among unemployed is not a mechanical result that arises due to changes in the composition of employed or the labor force, but instead arises due to the fact that separations move differentially over the business cycle for low- and high-wage workers.

Note that the conclusion above is based on the assumption that group-specific unemployment rates are held constant and do not change in response to changes in the composition of the labor force. Even if we assume that all transition rates in and out of unemployment are constant

[6] The latter is by assumption, as I divide the sample each year by the median wage. Note from the average group-specific unemployment rates reported in Table 2, one can compute the average shares of high-wage workers among the unemployed:

$$\phi_{high,t}^{U} = \frac{U_{high,t}}{U_{low,t} + U_{high,t}} = \frac{0.024}{0.024 + 0.045} = 0.35.$$

over the business cycle, group-specific unemployment may vary for two reasons: First, the flow steady state of unemployment rates depends on the transition rates between employment and out of the labor force. The reason is that movements between out of the labor force and employment changes the relative size of these pools and thus – if the flow rate from unemployment to employment is different from the flow rate from out of the labor force to unemployment – this can indirectly affect the unemployment rate (see Shimer, 2012). Second, transitional dynamics between flow steady states may lead to changes in group-specific unemployment rates.[7]

To make sure that the assumption of constant group-specific unemployment rates does not affect my conclusion above, I simulated a three-state model of the labor market with employment, unemployment and out of the labor force, where I vary the flow rate between out of the labor force and employment over the cycle and keep all other transition rates constant.[8] More specifically, I calibrated the average flow rates between the three states E(mploymnet), U(nemployment) and O(ut of the labor force) as follows: $f_{ue} = 0.31$, $f_{eu} = 0.0105$, $f_{oe} = 0.045$, $f_{eo} = 0.03$, $f_{ou} = 0.035$ and $f_{uo} = 0.25$. The first two transition rates match the averages in my CPS sample, whereas the other transition rates match the averages in Figure 3 shown in Elsby, Hobijn and Sahin (2015). To focus on how shifts in the composition of the employed affect the composition of the unemployed, in the simulations I assume that all rates are constant and the same for both groups, except for the flow rate between out of the labor force and employment. For the latter I assume that it increases for the high type (and for the high type only) from 0.045 to 0.05 in the bad aggregate state[9], and then analyze the effect of these changes on the composition of the pool of unemployed and employed. As to be expected, these simulations result in small shifts towards high-wage workers among the employed in the bad aggregate state. At the same time, these simulations show small shifts towards low-wage workers among the unemployed in the bad aggregate state, i.e. in the opposite direction of the pool of employed. The main reason is that shifts towards high-wage workers among the employed, actually lead to a reduction in the flow steady state unemployment rate of the high-wage workers as fewer high-wage workers directly transition from out of the labor force into unemployment (because there are fewer high-wage workers in the pool out of the labor force). These results reinforce the conclusion from above that shifts toward high-wage workers among the employed in recessions cannot explain the much larger magnitude of the compositional shifts among the unemployed. In fact, the simulations show that shifts towards high-wage workers may pull the pool of unemployed in the opposite direction of what I document in the data, if

[7] It is important to note here, first, that unemployment rates converge to their flow steady state relatively fast due to the high job finding rates. Shimer (2012) notes that in post-war U.S. data the correlation between the flow steady state unemployment rate and the actual unemployment rate is 0.99. Therefore, transitional dynamics are unlikely to change the results shown above.

[8] The codes of the simulation are available on request.

[9] This is consistent with the cyclical movements in this rate as shown in Figure 3 of Elsby, Hobijn and Sahin (2015).

these changes among the employed are driven by labor force entry or exit.[10]

In sum, I conclude that the much larger magnitude of the shifts among unemployed is not a mechanical result that arises due to changes in the composition of employed or changes in the composition of the labor forc), but instead arises due to the fact that separations move differentially over the business cycle for low- and high-wage workers.

B.2 Further evidence on compositional changes in separations and job findings

The Appendix Table B.2 shows the cyclicality of the ratios of separation and job finding rates from the CPS monthly files, both looking at transitions from month in sample 2 to 3 as well as using all months in the sample. The point estimates for the cyclicality of the ratios of separation rates suggest that inflows, in general, sort towards high-wage workers in times of high unemployment. The point estimates for the sample of rotation group 2 point in the same direction, and I cannot reject the equality of the coefficients between the two samples at the 5 percent level.

There is also some evidence of cyclicality in the ratios of group-specific job-finding rates, though the results are mixed and overall the magnitude appears to be smaller. On the one hand, the job finding rate of those with less than a high school degree relative to those with a high school degree increases and the ratio of job-finding rates of white to non-white decreases in times of high unemployment. This suggests that the composition of outflows sorts towards high-wage workers in recessions and can explain part of the compositional changes in the stock of unemployed. This is in line with the findings in the paper, which finds a slightly (but statistically not significantly) higher cyclicality of job-finding rates for high-wage groups relative to low-wage groups. On the other hand, the ratio of job-finding rates of those of age 50-59 to those of age 40-49 decreases in times of high unemployment, as does the ratio of those 30-39 to those 40-49. To the extent that those of age 30-39 and 50-59 are paid lower wages compared to those of age 40-49, this suggests that outflows sort towards low-wage individuals in times of high unemployment.

Overall, the sizes of the coefficients in Table B.2 are much larger for job-separation rates than for job finding-rates, suggesting that job separations are more cyclical than job-finding rates if one aggregates across groups. A quick (but imperfect) calculation confirms this: summing the cyclicality of the ratios in Table B.2 – assigning a positive weight (1) for high-wage groups in lines 4, 5, 6 and 8 and a negative weight (-1) for low-wage groups in lines 1 and 7 – gives 0.81 for the cyclicality of the ratios of separations (0.79 for the MIS=2 sample) and -0.20 for

[10] Note that in the simulations for simplicity I assume that the changes in the pool of unemployed are driven only by changes in the transition rate between out of the labor force and employment, f_{oe}, for the high type. The results are very similar if instead I assume that the changes are driven by changes in the transition rate between employment and out of the labor force, f_{eo}, for the high type.

the cyclicality of the ratios of job-finding rates (-0.24 for the MIS=2 sample). While this is, admittedly, a very imperfect way of aggregating the cyclicality of these ratios, it is in line with the main results shown in Table 2 of the paper, suggesting that it is mainly the cyclicality of job separations among high-wage individuals that drives the compositional changes in the pool of unemployed over the business cycle.

TABLE B.1 CYCLICALITY OF THE RATIOS UNEMPLOYMENT, EMPLOYMENT AND LABOR FORCE PARTICIPATION RATES

	Cyclicality of ratios of *unemployment* rates				Cyclicality of ratios of *employment* rates				Cyclicality of ratios of *LF participation* rates			
Ratio of:	All MIS		MIS=2		All MIS		MIS=2		All MIS		MIS=2	
Age 20-29 to Age 40-49	-0.18	(0.04)***	-0.22	(0.04)***	-0.04	(0.01)***	-0.04	(0.01)***	-0.02	(0.00)***	-0.02	(0.01)***
Age 30-39 to Age 40-49	0.02	(0.02)	0.00	(0.04)	-0.01	(0.00)***	-0.01	(0.00)***	0.00	(0.00)	-0.00	(0.00)
Age 50-59 to Age 40-49	0.05	(0.04)	0.03	(0.06)	0.00	(0.00)	0.00	(0.00)	0.00	(0.01)	-0.00	(0.01)
Married to Non-Married	0.30	(0.02)***	0.26	(0.02)***	0.04	(0.00)***	0.04	(0.00)***	0.02	(0.01)***	0.02	(0.01)***
Male to Female	0.36	(0.04)***	0.35	(0.04)***	-0.03	(0.00)***	-0.03	(0.00)***	-0.00	(0.01)	-0.00	(0.01)
White to Non-White	0.12	(0.05)**	0.11	(0.05)**	0.05	(0.01)***	0.05	(0.01)***	0.02	(0.01)***	0.02	(0.01)**
Less than HS degree to HS degree	-0.22	(0.03)***	-0.22	(0.03)***	-0.05	(0.00)***	-0.04	(0.01)***	-0.04	(0.01)***	-0.04	(0.01)***
More than HS degree to HS degree	0.05	(0.07)	0.09	(0.08)	0.04	(0.01)***	0.04	(0.01)***	0.00	(0.00)	0.00	(0.00)

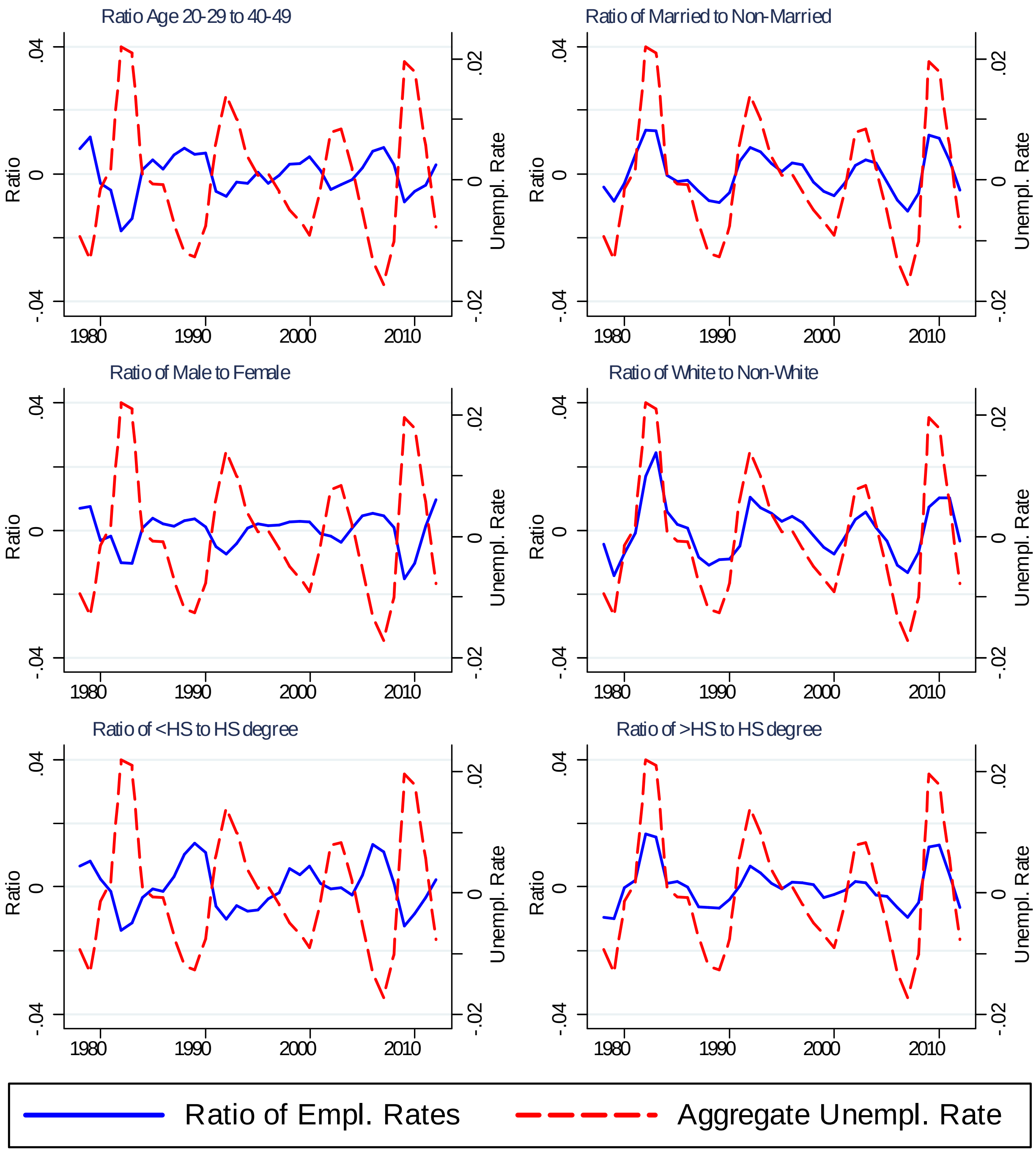
Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; MIS refers to month in sample; MIS=2 indicates that only data from the second interview out of the 8 interviews in the CPS were used for the estimates; All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cyclicality is measured as the coefficient β in the regression $\ln(U_{it}/U_{jt}) = \alpha + \beta \ln(U_t) + \varepsilon t$, where U_{it}/U_{jt} is the ratio of unemployment rates of group *i* and *j*, and U_t is the official unemployment rate from the Bureau of Labor Statistic. Source: The author's estimates with data from the CPS Monthly files for the years 1978-2012.

TABLE B.2 CYCLICALITY OF THE RATIOS SEPARATION AND JOB-FINDING RATES

	Cyclicality of ratios of *separation* rates				Cyclicality of ratios of *job-finding* rates			
Ratio of:	All MIS		MIS=2		All MIS		MIS=2	
Age 20-29 to Age 40-49	-0.11	(0.04)**	-0.27	(0.11)**	-0.02	(0.04)	-0.07	(0.09)
Age 30-39 to Age 40-49	0.04	(0.05)	-0.04	(0.10)	-0.07	(0.02)***	-0.21	(0.09)**
Age 50-59 to Age 40-49	0.01	(0.05)	-0.11	(0.18)	-0.10	(0.06)	-0.05	(0.11)
Married to Non-Married	0.27	(0.04)***	0.25	(0.06)***	-0.01	(0.04)	-0.04	(0.07)
Male to Female	0.29	(0.03)***	0.31	(0.08)***	-0.04	(0.03)	-0.02	(0.05)
White to Non-White	0.02	(0.06)	-0.10	(0.10)	-0.09	(0.03)**	-0.09	(0.06)
Less than HS degree to HS degree	-0.07	(0.04)*	-0.03	(0.07)	0.09	(0.02)***	0.10	(0.09)
More than HS degree to HS degree	0.05	(0.04)	0.03	(0.09)	0.01	(0.04)	-0.06	(0.06)

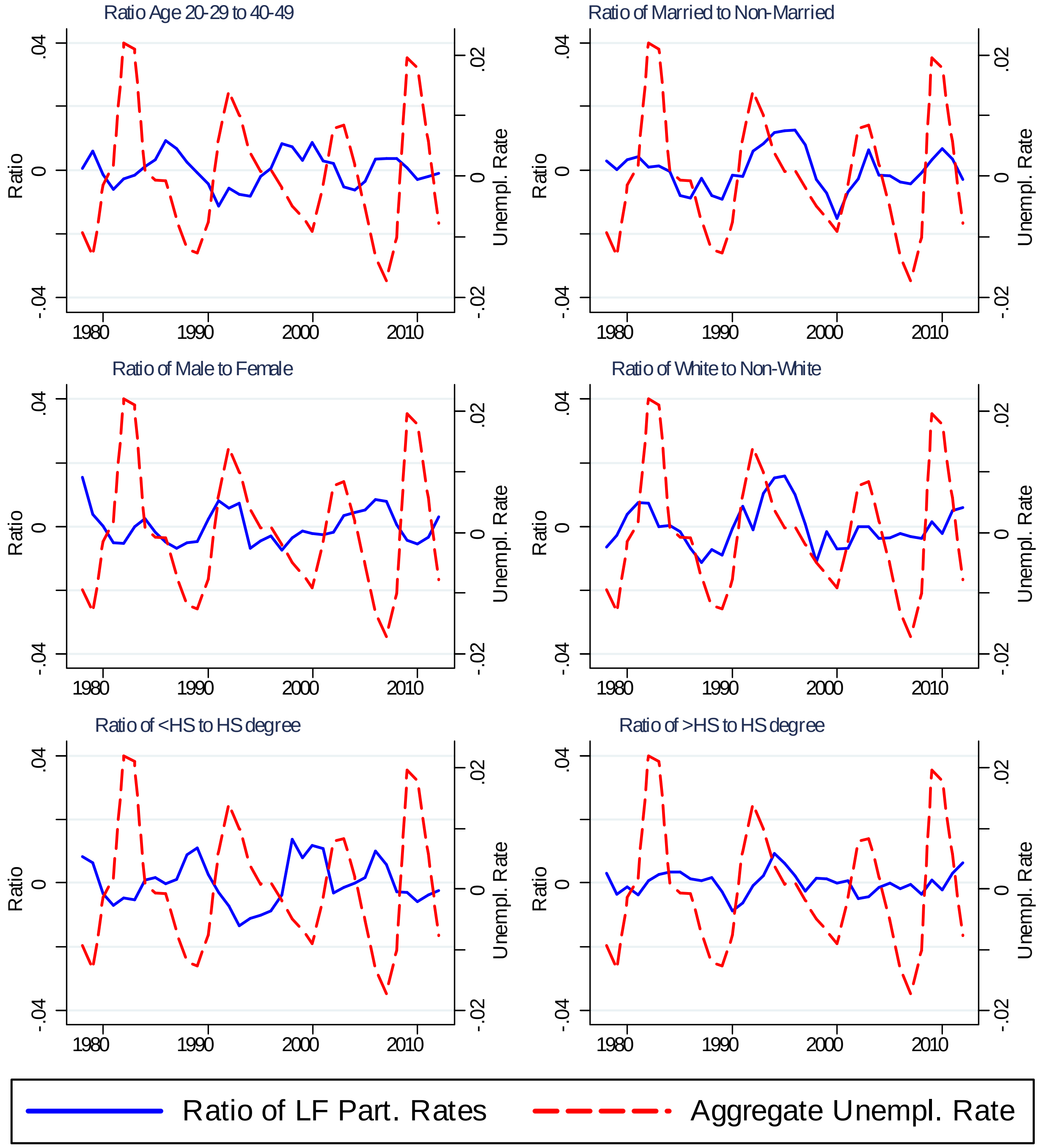
Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; MIS refers to month in sample; MIS=2 indicates that only data from the second interview out of the 8 interviews in the CPS were used for the estimates; All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cyclicality is measured as the coefficient β in the regression $\ln(x_{it}/x_{jt}) = \alpha + \beta \ln(U_t) + \varepsilon t$, where x_{it}/x_{jt} is the ratio of separation or job finding rates of group *i* and *j*, and U_t is the official unemployment rate from the Bureau of Labor Statistic. Source: The author's estimates with data from the CPS Monthly files for the years 1978-2012.

Figure 1: *Ratios of group-specific employment rates for the years 1978-2012*



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

Figure 2: *Ratios of group-specific labor force participation rates for the years 1978-2012*



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

Appendix C. Robustness checks for the empirical analysis

This Appendix provides additional robustness checks for the matched CPS ORG sample and the NLSY79:

1. Table C.1 provides additional estimates of the cyclicality of the average wage from the previous year for those currently unemployed in the matched CPS ORG sample for the years 1980 to 2012 (as line 1 in Table 1), for different sample restrictions (restricting the sample to those age 25-54, to men only, to those with some college education or more, to full-time workers only, excluding those in manufacturing or construction, or including those employed in the public sector), for different definitions of the pool of unemployed (including those out of the labor force and separate results by type of unemployed), for an HP-filter that allows for a more variable trend, and for different assumptions about the computation of the wage variable (computing the hourly wage based on hours worked last week instead of usual hours, computing the hourly wage with no imputations for those with missing hours, or winsorizing at 1.4 times the top code instead of trimming at $100 in 1979 dollars).

2. Tables C.2A, C.2B and C.3 compute the same robustness checks but for the cyclicality of the separation, job finding and unemployment rates for those below and above the median (residual) wage each year (the baseline estimates are those from Table 2 in the main text). In addition, Tables C.2A and C.2B include a robustness check where job finding and separation rates are adjusted for time aggregation as in Fujita and Ramey (2009).

3. 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 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 C.4 shows the average and the cyclicality of job-to-job transitions for the same groups as in Table 2 in the paper. 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 cyclicality of separations for high-wage workers is driven by the fact that direct job-to-job transitions

decrease strongly during recessions for this group. On the contrary, it appears that job-to-job transitions decrease more for low-wage workers in recessions and thus one would expect 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.

4. 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 C.4 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.

5. Table C.5 provides the same estimates as in Table 2 in the main text but dividing the sample by quartile each year (instead of below and above the median wage each year). In addition, Panel (a) of Figure **??** shows the densities of the unemployed by percentile of the distribution wages in the previous year. It shows that, in periods of low unemployment, the pool of unemployed is strongly skewed towards the lower part of the distribution of wages, whereas this is much less true in periods of high unemployment. Interestingly, even the share of individuals in the top quartile increases in periods of high unemployment. In fact, in periods of high unemployment, the density looks almost like a uniform density, which suggests that the unemployed in recessions are similar to the average employed person.[11] The same patterns hold true when looking at the distribution of residual wages (see Panel (b)).

6. 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

[11] Note that, by definition, the densities follow the uniform distribution for the full sample (i.e., all those employed in the previous year).

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+).[12] I then take the residual of this regression and compute the average wage residual among the unemployed in each year. The results reported in Appendix Table C.6A show that the compositional changes in the pool of unemployed in terms of the residual wage are not affected at all by controlling for employer size in the wage regression.[13]

7. Table C.6B reports additional results of the average and cyclicality of the unemployment rate and short-term unemployment rate by the size of employer on the job in the prior year. Consistent with Shimer (2005), I define short-term unemployed as any individual who is unemployed at the time of the CPS March interview with duration of unemployment of 4 weeks or less. The short-term unemployment rate should indicate whether the results w.r.t. to employer size are driven by inflows or outflows. As argued by several authors (Elsby et al., 2011, and Rothstein, 2011), however, unemployment duration of 4 weeks or less is a good measure of inflows for the period before 2008 but not thereafter. Therefore, I excluded the years 2008-2012 for this analysis (the results are very similar if I include the years 2008-2012).The analysis reveals that the cyclicality of unemployment is slightly higher among workers with small employers in the prior year, and the cyclicality of the ratio of unemployment of those who worked at large employers compared to those who worked at the small employers is slightly negative and only marginally significant. This suggests that – if anything – the pool of unemployed moves towards workers who worked at small employers in recessions, in line with the results presented in Appendix Table C.6A. Table C.6A shows that the pool of unemployed moves slightly towards workers who worked at low-wage (=smaller) firms, although the coefficient is not significant. The results in Table C.6B also hold for the short-term unemployment rate, indicating that separations increase somewhat more than proportionally at smaller firms in recessions.

8. Table C.7 provides an analysis that holds the composition by type of unemployed (on layoff, job loser, job leaver and new or re-entrant) constant over time. The results show

[12] 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.

[13] 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 hiring 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. In fact, in a more recent paper Moscarini and Postel-Vinay (2014) present evidence on gross flows in the great recession and show that hire rates dropped sharply at larger establishments relative to hire rates at smaller establishments.

that 75 percent of the patterns in the raw wage and more than 90 percent of the patterns in the residual wage are explained by compositional changes *within* types. These results are obtained by dividing, in each panel, the coefficient in row 2 by the coefficient in row 1. The fact that the contribution of types of unemployed to compositional changes is smaller for the residual wage can be explained by the fact that types of unemployed are captured to a large extent by observable characteristics (in particular, age, gender and industry).

9. Table C.8 shows additional robustness checks to investigate the role of attrition in the CPS ORG data. I estimated the cyclicality of separation and job finding rates for rotations 5, 6 and 7 separately, and report the results in the new Appendix Table C.8. The results show that the cyclicality of separations and job findings is very similar for MIS 5, 6, 7 and the full (baseline) sample. I also estimated the cyclicality of separation and job finding rates with a different set of weights where I added a polynomial of degree 3 of the log of the prior in the attrition model (in addition to the demographics). The results in Appendix Table C.8 show that this makes hardly any difference for the estimates of the cyclicality of separation and job finding rates by wage group. The results are also very similar when I do not adjust for attrition at all.

10. Table C.9 provides additional evidence on the cyclicality of attrition rates by wage group in the CPS ORG data. Attrition is defined as an indicator whether labor for status was missing in a given MIS for those in my baseline sample (i.e., those who are employed in MIS 4). Note that I did use survey weights that do *not* adjust for attrition when computing the cyclicality of attrition rates. The results show that in general there is a mild pro-cyclicality of attrition, but the pro-cyclicality is very similar between the low- and high-wage group (and differences are never statistically significant). In short, the additional evidence shows that there is little or no selective attrition by wage group over the business cycle and, as a consequence, it makes little difference for the main estimates in the paper whether one adjusts for attrition by adjusting survey weights or whether one restricts the sample to rotations with less attrition (in Table C.8).

11. Table C.10 provides robustness checks for the estimates from the NLSY79 reported in Table 1 in the paper.

12. Table C.11 provides estimates of the cyclicality of separation, job finding and unemployment rates by wage group with the NLSY79. The results confirm the analysis in the CPS ORG data, namely that the compositional changes in the pool of unemployed over the business cycle are driven by separations and not job findings. More precisely, the cyclicality of separations is significantly higher in the high-wage group compared to the low-wage group, whereas the cyclicality of job finding rates is not significantly different

across groups (and in fact, the point estimate points towards a slightly *lower* cyclicality of job findings for the high-wage group). In addition, the table shows the cyclicality of separation and job finding rates for those below and above the unobserved fixed effect and for those below and above the unobserved transitory effect. The results show that the cyclicality of separations is higher for those with high unobserved fixed effects, but exactly the same for those below and above the median unobserved transitory effect.

TABLE C.1 THE COMPOSITIONAL CHANGES IN THE POOL OF UNEMPLOYED, ADDITIONAL ESTIMATES ON THE CYCLICALITY OF THE AVERAGE WAGE FROM THE PREVIOUS YEAR

	Raw wage	Predicted wage	Residual wage	Wage rank
Baseline (Unemployed)	2.77	2.01	0.75	1.45
	(0.51)***	(0.38)***	(0.20)***	(0.26)***
Sample:				
Subsample: Age 25 - 54	2.46	1.63	0.84	1.27
	(0.50)***	(0.30)***	(0.29)***	(0.24)***
Subsample: Men only	2.66	1.84	0.82	1.42
	(0.64)***	(0.38)***	(0.32)**	(0.30)***
Subsample: Some college or more	2.57	1.73	0.85	1.26
	(0.60)***	(0.33)***	(0.36)**	(0.27)***
Subsample: Full-time workers	2.41	1.70	0.71	1.30
	(0.52)***	(0.34)***	(0.24)***	(0.27)***
Subsample: Not manufacturing and not construction	2.69	1.88	0.81	1.40
	(0.51)***	(0.36)***	(0.21)***	(0.25)***
Extended sample: Including public sector employees	2.68	2.00	0.68	1.35
	(0.45)***	(0.34)***	(0.20)***	(0.21)***
Including those out of the labor force and by type of unemployed:				
Unemployed AND out of the labor force	2.13	1.63	0.50	1.13
	(0.28)***	(0.23)***	(0.10)***	(0.14)***
Unemployed but not on temporary layoff	2.77	2.08	0.69	1.43
	(0.64)***	(0.45)***	(0.30)**	(0.31)***
Unemployed, on temporary layoff	2.52	1.40	1.11	1.47
	(0.74)***	(0.54)**	(0.58)*	(0.40)***
Unemployed, job loser	2.55	1.76	0.79	1.31
	(0.77)***	(0.54)***	(0.38)**	(0.36)***
Unemployed, job leaver	0.92	0.21	1.13	0.35
	(0.48)*	(0.47)	(0.49)**	(0.23)
Unemployed, new or re-entrant	0.53	0.80	0.27	0.08
	(0.80)	(0.80)	(0.80)	(0.80)
Additional robustness checks:				
Filtering: HP-filtered with smoothing parameter 6.25	2.92	2.28	0.64	1.55
	(0.49)***	(0.42)***	(0.17)***	(0.25)***
Cyclical variable: Unemployment rate (instrumented by log of real GDP)	2.64	1.89	0.76	1.37
	(0.44)***	(0.39)***	(0.19)***	(0.19)***
State-level analysis: Regressing state-level wage on state-level unemployment rate	2.23	1.56	0.67	1.18
	(0.30)***	(0.23)***	(0.18)***	(0.16)***
Hourly wage: Based on hours worked last week	2.63	2.01	0.62	1.42
	(0.50)***	(0.38)***	(0.19)***	(0.25)***
Hourly wage: No imputation for missing hours	2.72	1.98	0.74	1.44
	(0.51)***	(0.37)***	(0.21)***	(0.26)***
Hourly wage: Windsorized at 1.4 times the top code instead of trimmed at $100 in 1979 dollars	2.76	2.01	0.75	1.46
	(0.53)***	(0.38)***	(0.21)***	(0.26)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are yearly averages, HP-filtered with a smoothing parameter of 100, unless otherwise stated. The cylicality is measured as the coefficient β in the regression $\log(w^u_t) - \log(w_t) = \alpha + \beta U_t + \varepsilon_t$, where w^u_t 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 Statistic. Note that the coefficients on the predicted and residual wage do add up to the coefficient on the raw wage. Source: The author's estimates with data from the matched CPS ORG sample for the years 1980 to 2012.

TABLE C.2A THE CYCLICALITY OF SEPARATION RATES, BY WAGE GROUP (ROBUSTNESS CHECKS)

	A. Based on hourly wage		*B. Based on Mincer residual*	
	Low	High	Low	High
Baseline	0.32 (0.09)***	0.74 (0.09)***	0.42 (0.07)***	0.60 (0.08)***
Sample:				
Subsample: Age 25 - 54	0.36 (0.07)***	0.72 (0.09)***	0.42 (0.07)***	0.64 (0.08)***
Subsample: Men only	0.40 (0.07)***	0.75 (0.11)***	0.47 (0.07)***	0.63 (0.10)***
Subsample: Some college or more	0.36 (0.08)***	0.75 (0.14)***	0.42 (0.09)***	0.68 (0.11)***
Subsample: Full-time workers	0.35 (0.09)***	0.74 (0.10)***	0.43 (0.07)***	0.61 (0.10)***
Subsample: Not manufacturing and not construction	0.31 (0.09)***	0.73 (0.09)***	0.40 (0.07)***	0.62 (0.08)***
Extended sample: Including public sector employees	0.30 (0.08)***	0.75 (0.11)***	0.40 (0.07)***	0.60 (0.09)***
Including those out of the labor force and by type of unemployed:				
Unemployed AND out of the labor force	0.06 (0.04)	0.40 (0.07)***	0.15 (0.05)***	0.24 (0.06)***
Unemployed but not on temporary layoff	0.37 (0.11)***	0.73 (0.12)***	0.43 (0.08)***	0.62 (0.09)***
Unemployed, on temporary layoff	0.24 (0.13)*	0.81 (0.17)***	0.44 (0.14)***	0.59 (0.18)***
Unemployed, job loser	0.72 (0.13)***	1.03 (0.14)***	0.76 (0.10)***	1.00 (0.12)***
Unemployed, job leaver	0.69 (0.18)***	0.79 (0.28)***	0.94 (0.19)***	0.37 (0.19)*
Unemployed, new or re-entrant	0.05 (0.25)	0.06 (0.35)	0.27 (0.29)	0.04 (0.22)
Additional robustness checks:				
Filtering: HP-filtered with smoothing parameter 14400	0.29 (0.09)***	1.02 (0.09)***	0.46 (0.09)***	0.80 (0.09)***
Adjusted for time aggregation bias	0.21 (0.09)***	0.61 (0.09)***	0.30 (0.09)***	0.48 (0.09)***
Hourly wage: Based on hours worked last week	0.32 (0.09)***	0.74 (0.09)***	0.43 (0.07)***	0.58 (0.09)***
Hourly wage: No imputation for missing hours	0.33 (0.09)***	0.73 (0.09)***	0.43 (0.08)***	0.59 (0.08)***
Hourly wage: Windsorized at 1.4 times the top code instead of trimmed at $100 in 1979 dollars.	0.32 (0.09)***	0.75 (0.10)***	0.42 (0.07)***	0.60 (0.08)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000, unless otherwise noted. The cylicality is measured as the coefficient β in the regression $\ln(s_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where s_{it} is the separation 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.

TABLE C.2B THE CYCLICALITY OF JOB FINDING RATES, BY WAGE GROUP (ROBUSTNESS CHECKS)

	A. Based on hourly wage		*B. Based on Mincer residual*	
	Low	High	Low	High
Baseline	-0.55 (0.05)***	-0.62 (0.07)***	-0.63 (0.06)***	-0.54 (0.07)***
Sample:				
Subsample: Age 25 - 54	-0.49 (0.07)***	-0.53 (0.08)***	-0.55 (0.09)***	-0.51 (0.06)***
Subsample: Men only	-0.53 (0.04)***	-0.58 (0.07)***	-0.58 (0.06)***	-0.53 (0.07)***
Subsample: Some college or more	-0.57 (0.06)***	-0.53 (0.10)***	-0.64 (0.08)***	-0.47 (0.11)***
Subsample: Full-time workers	-0.55 (0.05)***	-0.59 (0.07)***	-0.58 (0.07)***	-0.53 (0.07)***
Subsample: Not manufacturing and not construction	-0.59 (0.07)***	-0.59 (0.11)***	-0.64 (0.08)***	-0.55 (0.10)***
Extended sample: Including public sector employees	-0.58 (0.05)***	-0.64 (0.07)***	-0.63 (0.06)***	-0.57 (0.07)***
Including those out of the labor force and by type of unemployed:				
Unemployed AND out of the labor force	-0.26 (0.06)***	-0.40 (0.05)***	-0.30 (0.05)***	-0.33 (0.05)***
Unemployed but not on temporary layoff	-0.66 (0.06)***	-0.77 (0.09)***	-0.74 (0.07)***	-0.66 (0.09)***
Unemployed, on temporary layoff	-0.33 (0.13)**	-0.36 (0.11)***	-0.36 (0.11)***	-0.33 (0.09)***
Unemployed, job loser	-0.65 (0.10)***	-0.57 (0.11)***	-0.61 (0.12)***	-0.69 (0.12)***
Unemployed, job leaver	-0.51 (0.14)***	-0.74 (0.22)***	-0.90 (0.16)***	-0.42 (0.16)***
Unemployed, new or re-entrant	-0.57 (0.11)***	-0.30 (0.24)	-0.69 (0.19)***	-0.57 (0.16)***
Additional robustness checks:				
Filtering: HP-filtered with smoothing parameter 14400	-0.58 (0.05)***	-0.60 (0.05)***	-0.61 (0.05)***	-0.61 (0.05)***
Adjusted for time aggregation bias	-0.66 (0.05)***	-0.75 (0.05)***	-0.75 (0.05)***	-0.66 (0.05)***
Hourly wage: Based on hours worked last week	-0.55 (0.05)***	-0.62 (0.08)***	-0.62 (0.06)***	-0.56 (0.06)***
Hourly wage: No imputation for missing hours	-0.55 (0.05)***	-0.62 (0.08)***	-0.62 (0.06)***	-0.55 (0.07)***
Hourly wage: Windsorized at 1.4 times the top code instead of trimmed at $100 in 1979 dollars.	-0.55 (0.05)***	-0.62 (0.08)***	-0.62 (0.06)***	-0.54 (0.07)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000, unless otherwise noted. The cylicality is measured as the coefficient β in the regression $\ln(f_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where f_{it} is the job finding 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.

TABLE C.3 THE CYCLICALITY OF UNEMPLOYMENT RATES, BY WAGE GROUP (ROBUSTNESS CHECKS)

	A. Based on hourly wage		*B. Based on Mincer residual*	
	Low	High	Low	High
Baseline	0.79 (0.03)***	1.31 (0.04)***	0.91 (0.02)***	1.11 (0.03)***
Sample:				
Subsample: Age 25 - 54	0.83 (0.03)***	1.25 (0.04)***	0.92 (0.03)***	1.11 (0.04)***
Subsample: Men only	0.84 (0.03)***	1.28 (0.05)***	0.92 (0.03)***	1.11 (0.04)***
Subsample: Some college or more	0.85 (0.03)***	1.20 (0.05)***	0.96 (0.04)***	1.06 (0.05)***
Subsample: Full-time workers	0.82 (0.03)***	1.28 (0.05)***	0.92 (0.03)***	1.10 (0.03)***
Subsample: Not manufacturing and not construction	0.79 (0.03)***	1.30 (0.04)***	0.90 (0.03)***	1.12 (0.03)***
Extended sample: Including public sector employees	0.80 (0.03)***	1.33 (0.05)***	0.91 (0.03)***	1.12 (0.03)***
Including those out of the labor force and by type of unemployed:				
Unemployed AND out of the labor force	0.27 (0.03)***	0.69 (0.04)***	0.36 (0.02)***	0.49 (0.04)***
Unemployed but not on temporary layoff	0.82 (0.03)***	1.36 (0.06)***	0.94 (0.03)***	1.14 (0.04)***
Unemployed, on temporary layoff	0.66 (0.10)***	1.24 (0.13)***	0.84 (0.10)***	1.03 (0.11)***
Unemployed, job loser	1.17 (0.06)***	1.63 (0.07)***	1.27 (0.05)***	1.52 (0.06)***
Unemployed, job leaver	0.08 (0.12)	0.15 (0.25)	0.08 (0.12)	0.17 (0.16)
Unemployed, new or re-entrant	0.41 (0.08)***	0.72 (0.22)***	0.45 (0.10)***	0.51 (0.10)***
Additional robustness checks:				
Filtering: HP-filtered with smoothing parameter 14400	0.77 (0.03)***	1.30 (0.03)***	0.90 (0.03)***	1.11 (0.03)***
Hourly wage: Based on hours worked last week	0.80 (0.03)***	1.30 (0.04)***	0.92 (0.02)***	1.10 (0.03)***
Hourly wage: No imputation for missing hours	0.79 (0.03)***	1.30 (0.04)***	0.91 (0.02)***	1.11 (0.03)***
Hourly wage: Windsorized at 1.4 times the top code instead of trimmed at $100 in 1979 dollars.	0.79 (0.03)***	1.31 (0.04)***	0.91 (0.03)***	1.11 (0.03)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000, unless otherwise noted. The cylicality is measured as the coefficient β in the regression $\ln(U_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where U_{it} is the 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.

TABLE C4. THE CYCLICALITY OF JOB-TO-JOB TRANSITIONS AND MOVEMENTS FROM UNEMPLOYMENT (U) TO OUT OF THE LABOR FORCE (OLF), BY WAGE GROUP

		A. Based on hourly wage		*B. Based on Mincer residual*	
		Low	High	Low	High
Job-to-job transitions	Average	0.027	0.018	0.024	0.020
	Cyclicality	**-0.35**	**-0.18**	**-0.27**	**-0.27**
(1994-2012 only)	(s.e.)	(0.07)***	(0.07)***	(0.07)***	(0.06)***
Transitions from U to OLF	Average	0.133	0.068	0.112	0.098
	Cyclicality	**-0.35**	**-0.24**	**-0.44**	**-0.37**
	(s.e.)	(0.07)***	(0.13)*	(0.09)***	(0.11)***

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.

TABLE C.5 THE CYCLICALITY OF SEPARATION, JOB FINDING AND UNEMPLOYMENT RATES, BY WAGE GROUP (QUARTILES)

		A. Quartiles based on hourly wage			
		1st	***2nd***	***3rd***	***4th***
Separation rates	**Cyclicality**	**0.24**	**0.40**	**0.72**	**0.84**
	(s.e.)	(0.11)**	(0.12)***	(0.12)***	(0.13)***
Job finding rates	**Cyclicality**	**-0.50**	**-0.60**	**-0.61**	**-0.60**
	(s.e.)	(0.06)***	(0.10)***	(0.10)***	(0.11)***
Unemployment rates	**Cyclicality**	**0.60**	**1.00**	**1.23**	**1.41**
	(s.e.)	(0.04)***	(0.04)***	(0.07)***	(0.06)***
		B. Quartiles based on Mincer residual			
		1st	***2nd***	***3rd***	***4th***
Separation rates	**Cyclicality**	**0.37**	**0.48**	**0.60**	**0.65**
	(s.e.)	(0.11)***	(0.09)***	(0.09)***	(0.11)***
Job finding rates	**Cyclicality**	**-0.62**	**-0.63**	**-0.50**	**-0.61**
	(s.e.)	(0.07)***	(0.10)***	(0.08)***	(0.08)***
Unemployment rates	**Cyclicality**	**0.91**	**0.93**	**1.04**	**1.20**
	(s.e.)	(0.04)***	(0.05)***	(0.04)***	(0.06)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000. The cylicality is measured as the coefficient β in the regression $\ln(x_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where x_{it} is the separation, the job finding or the 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.

TABLE C.6A COMPOSITIONAL CHANGES IN THE POOL OF UNEMPLOYED, BY PREDICTED AND RESIDUAL WAGE (CONTROLLING FOR EMPLOYER SIZE)

	Raw wage	*A. Baseline Decomposition*		*B. Controlling for employer size in the wage regression*		
		Predicted	Residual	Predicted (by all but employer size)	Predicted (by employer size)	Residual
CPS March (1968-2012)						
Cyclicality	2.59	1.64	0.95	---	---	---
(S.e.)	(0.28)***	(0.19)***	(0.13)***			
CPS March (1989-2012)						
Cyclicality	2.66	1.75	0.91	1.72	-0.03	0.96
(S.e.)	(0.48)***	(0.34)***	(0.18)***	(0.32)***	(0.03)	(0.19)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cylicality is measured as the coefficient β in the regression $\log(w^u_t) - \log(w_t) = \alpha + \beta U_t + \varepsilon_t$, where w^u_t 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 Statistic. Note that the coefficients on the predicted and residual wage add up to the coefficient on the raw wage. The estimates in Panel B are based on a Mincer wage regression which controls for employer size of the longest job held in the prior year (0-99, 100-499, 500-999, 1000+ employees). Source: The author's estimates with data from the CPS march supplement for the years 1989 to 2012.

TABLE C.6B THE CYCLICALITY OF UNEMPLOYMENT AND SHORT-TERM UNEMPLOYMENT, BY EMPLOYER SIZE CLASS ON JOB IN PRIOR YEAR

	Employer size class (number of employees):			
	0-99	100-499	500+	Ratio (firms of size 500+ to firms of size 0-99)
Unemployment rate				
Mean	0.047	0.038	0.028	
Cyclicality	1.06	0.93	0.92	-0.14
(S.e.)	(0.03)***	(0.07)***	(0.05)***	(0.07)*
Short-term unemployment rate				
Mean	0.016	0.013	0.010	
Cyclicality	0.74	0.60	0.47	-0.27
(S.e.)	(0.12)***	(0.16)***	(0.18)***	(0.14)**

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cylicality is measured as the coefficient β in the regression $\ln(x_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where x_{it} is the unemployment rate or short-term unemployment rate of group i at time t and U_t is the unemployment rate in the full sample. I instrument the sample unemployment rate with the official unemployment rate because of possible attenuation bias due to measurement error. The *short-term unemployment rate* is defined here as the fraction of the labor force which is unemployed with duration of unemployment of 4 weeks or less. Source: The author's estimates with data from the CPS march supplement for the years 1989 to 2007.

TABLE C.7 THE CYCLICALITY OF THE PRIOR WAGE OF THE UNEMPLOYED, HOLDING COMPOSITION *OF* AND *WITHIN* TYPES CONSTANT

	A. Based on hourly wage	*B. Based on Mincer residual*
4 types of unemployed, years 1980-2012	Cyclicality	Cyclicality
Baseline	2.77	0.75
	(0.51)***	(0.20)***
Holding composition *of* types constant	2.10	0.75
	(0.40)***	(0.25)**
Holding composition *within* types constant	0.64	0.07
	(0.25)**	(0.02)***
6 types of unemployed, years 1994-2012		
Baseline	2.68	0.58
	(0.40)***	(0.40)***
Holding composition *of* types constant	2.14	0.62
	(0.40)***	(0.40)***
Holding composition *within* types constant	0.25	0.06
	(0.40)***	(0.40)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are yearly averages, HP-filtered with a smoothing parameter of 100. The cylicality is measured as the coefficient β in the regression $\log(w^u_t) - \log(w_t) = \alpha + \beta U_t + \varepsilon_t$, where w^u_t 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 Statistic. I computed two alternative times series of the average wage in the prior year: The first measure holds the composition *of* types constant by computing the average share of each type over the entire sample period and multiplying the average shares with the type-specific pre-separation wage for each year, and then adding them up across all types. The second measure holds the composition *within* types constant by computing the average pre-separation wage for each type over the entire sample period and multiplying it by the share of each type in each year, and then adding them up across all types. Note that due to the redesign of the CPS in 1994, I show, for the period 1994-2012, the results of the analysis with six types of unemployed (on layoff, job loser, temporary job ended, job leaver, re-entrant and new entrant) and, for the period 1980-2012, I show the results of the analysis with four types of unemployed (on layoff, job loser, job leaver and new or re-entrant). Source: The author's estimates with data from the matched CPS ORG sample for the years 1980 to 2012.

TABLE C.8 THE CYCLICALITY OF SEPARATIONS, JOB FINDINGS AND UNEMPLOYMENT RATES, BY WAGE GROUP (ADDITIONAL ROBUSTNESS CHECKS TO INVESTIGATE THE ROLE OF ATTRITION)

	A. Based on hourly wage		*B. Based on Mincer residual*	
The cyclicality of separation rates	Low	High	Low	High
Baseline	0.32 (0.09)***	0.74 (0.09)***	0.42 (0.07)***	0.60 (0.08)***
Subsample: Transitions between MIS 5 and 6 only	0.32 (0.13)**	0.83 (0.14)***	0.44 (0.13)***	0.62 (0.13)***
Subsample: Transitions between MIS 6 and 7 only	0.40 (0.09)***	0.70 (0.10)***	0.45 (0.08)***	0.61 (0.10)***
Subsample: Transitions between MIS 7 and 8 only	0.30 (0.14)**	0.80 (0.12)***	0.41 (0.15)***	0.69 (0.10)***
Alternative weights: Not adjusting for attrition	0.33 (0.09)***	0.72 (0.09)***	0.43 (0.07)***	0.60 (0.08)***
Alternative weights: Adjusting for attrition based on demographics AND prior wage	0.32 (0.09)***	0.74 (0.09)***	0.42 (0.07)***	0.60 (0.08)***
The cyclicality of job finding rates	Low	High	Low	High
Baseline	-0.55 (0.05)***	-0.62 (0.07)***	-0.63 (0.06)***	-0.54 (0.07)***
Subsample: Transitions between MIS 5 and 6 only	-0.54 (0.08)***	-0.61 (0.10)***	-0.64 (0.09)***	-0.54 (0.09)***
Subsample: Transitions between MIS 6 and 7 only	-0.56 (0.08)***	-0.61 (0.09)***	-0.62 (0.08)***	-0.59 (0.08)***
Subsample: Transitions between MIS 7 and 8 only	-0.55 (0.09)***	-0.69 (0.09)***	-0.61 (0.08)***	-0.58 (0.11)***
Alternative weights: Not adjusting for attrition	-0.53 (0.05)***	-0.63 (0.07)***	-0.61 (0.06)***	-0.56 (0.05)***
Alternative weights: Adjusting for attrition based on demographics AND prior wage	-0.55 (0.05)***	-0.62 (0.08)***	-0.63 (0.06)***	-0.54 (0.07)***
The cyclicality of unemployment rates	Low	High	Low	High
Baseline	0.79 (0.03)***	1.31 (0.04)***	0.91 (0.02)***	1.11 (0.03)***
Subsample: Mis 5	0.79 (0.03)***	1.35 (0.05)***	0.93 (0.04)***	1.10 (0.06)***
Subsample: Mis 6	0.80 (0.03)***	1.28 (0.05)***	0.94 (0.03)***	1.10 (0.04)***
Subsample: Mis 7	0.79 (0.03)***	1.31 (0.04)***	0.91 (0.02)***	1.11 (0.03)***
Subsample: Mis 8	0.78 (0.03)***	1.33 (0.05)***	0.91 (0.04)***	1.14 (0.04)***
Alternative weights: Not adjusting for attrition	0.78 (0.03)***	1.28 (0.03)***	0.92 (0.02)***	1.10 (0.03)***
Alternative weights: Adjusting for attrition based on demographics AND prior wage	0.79 (0.03)***	1.31 (0.04)***	0.92 (0.02)***	1.11 (0.03)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000, unless otherwise noted. 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. 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.

TABLE C.9 THE CYCLICALITY OF ATTRITION IN THE CPS ORG DATA, BY WAGE GROUP AND MONTH IN SAMPLE

	A. Based on hourly wage		*B. Based on Mincer residual*	
	Low	High	Low	High
Attrition in any MIS (5, 6, 7 or 8)	-0.09	-0.10	-0.11	-0.08
	(0.05)*	(0.06)	(0.05)**	(0.06)
Attrition in MIS 5	-0.08	-0.09	-0.09	-0.08
	(0.05)	(0.07)	(0.06)	(0.06)
Attrition in MIS 6	-0.09	-0.10	-0.11	-0.09
	(0.05)*	(0.06)	(0.05)**	(0.06)
Attrition in MIS 7	-0.08	-0.10	-0.10	-0.08
	(0.05)*	(0.06)	(0.05)*	(0.06)
Attrition in MIS 8	-0.08	-0.08	-0.10	-0.07
	(0.04)*	(0.06)	(0.05)**	(0.05)

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000, unless otherwise noted. The cyclicality is measured as the coefficient β in the regression $\ln(a_{it}) = \alpha + \beta \ln(U_t) + \varepsilon_t$, where a_{it} is the separation 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. The attrition rate is defined as an indicator for whether information on labor force status was available in a given interview. Sample size: 370 monthly observations. Source: The author's estimates with data from the matched CPS ORG sample for the years 1980 to 2012.

TABLE C.10 THE COMPOSITIONAL CHANGES IN THE POOL OF UNEMPLOYED (ADDITIONAL ESTIMATES FROM THE NLSY79)

	Raw wage	Residual		
		Total	Fixed effect	Transitory effect
Baseline	2.08 (0.45)***	1.16 (0.57)**	0.77 (0.16)***	0.38 (0.48)
Subsample: Age 20 and older	2.46 (0.47)***	1.21 (0.40)***	0.86 (0.17)***	0.39 (0.46)
Subsample: Excluding the supplemental sample (poor households)	1.71 (0.40)***	1.09 (0.65)*	0.63 (0.13)***	0.45 (0.59)
Subsample: 15 wage observations or more (instead of 10 or more)	2.14 (0.59)***	1.30 (0.66)**	0.90 (0.13)***	0.27 (0.52)
Subsample: 5 wage observations or more (instead of 10 or more)	2.27 (0.51)***	1.11 (0.49)**	0.85 (0.17)***	0.26 (0.38)
Subsample: Individuals who held at least 5 different jobs	2.00 (0.48)***	1.07 (0.56)*	0.74 (0.17)***	0.31 (0.46)
Filtering: HP-filtered with smoothing parameter 6.25	2.65 (0.44)***	1.52 (0.48)***	0.93 (0.20)***	0.59 (0.45)

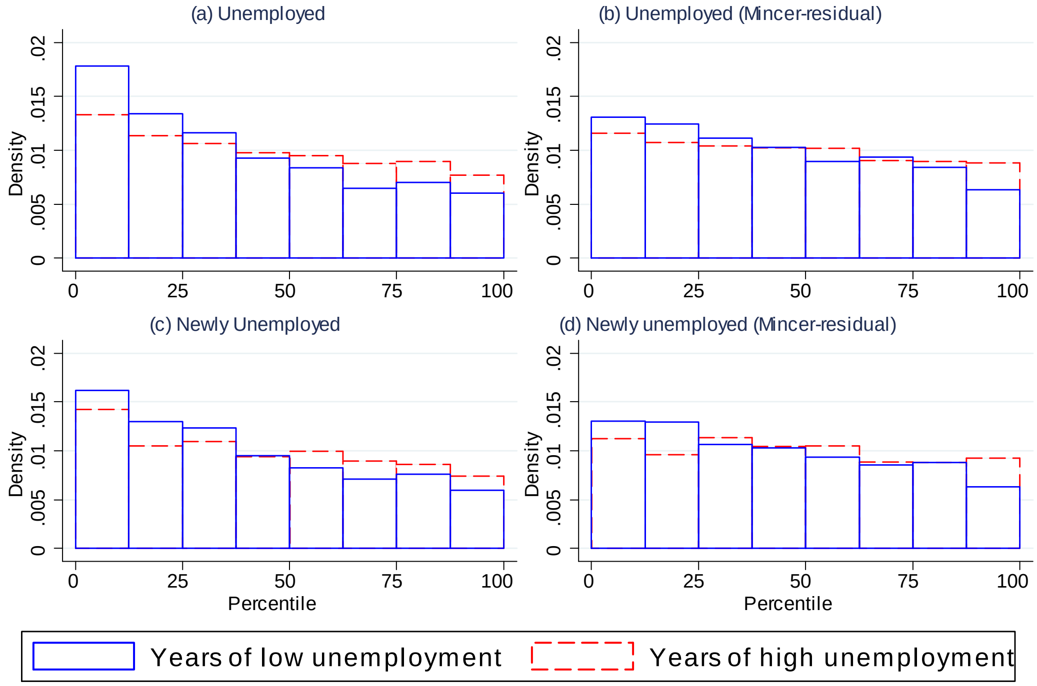
Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are yearly averages, HP-filtered with a smoothing parameter of 100, unless otherwise stated. The cylicality is measured as the coefficient β in the regression $\log(w^u_t) - \log(w_t) = \alpha + \beta U_t + \varepsilon_t$, where w^u_t 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 Statistic. Source: The author's estimates with data from the NLSY79 for the years 1979 to 2011.

TABLE C.11 THE CYCLICALITY OF SEPARATION, JOB FINDING AND UNEMPLOYMENT RATES IN THE NLSY79, BY WAGE GROUP (BELOW AND ABOVE MEDIAN)

		A. Based on hourly wage		*B. Based on unobserved fixed effect*		*C. Based on unobserved transitory effect*	
		Low	High	Low	High	Low	High
Separation rates	Average	0.011	0.007	0.011	0.007	0.008	0.008
	Cyclicality	**0.35**	**0.65**	**0.38**	**0.64**	**0.44**	**0.44**
	(s.e.)	(0.11)***	(0.10)***	(0.10)***	(0.11)***	(0.10)***	(0.14)***
Job finding rates	Average	0.191	0.215	0.177	0.187	0.196	0.209
	Cyclicality	**-0.49**	**-0.38**	**-0.47**	**-0.35**	**-0.57**	**-0.38**
	(s.e.)	(0.12)***	(0.08)***	(0.10)***	(0.09)***	(0.12)***	(0.08)***
Unemployment rates	Average	0.048	0.027	0.051	0.031	0.037	0.034
	Cyclicality	**0.87**	**1.21**	**0.90**	**1.16**	**1.06**	**0.93**
	(s.e.)	(0.03)***	(0.04)***	(0.04)***	(0.06)***	(0.04)***	(0.05)***

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 100. The cylicality 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 job finding and separation rates are computed at the monthly frequency, and then averaged over the entire year to avoid small or empty cells. In addition, I instrument the sample unemployment rate with the official unemployment rate because of possible attenuation bias due to measurement error. Sample size: 33 yearly observations. Source: The author's estimates with data from the NLSY79 for the years 1979 to 2011.

Figure 3: *Density of unemployed by percentile in the wage distribution from previous year*



Years of high unemployment = 1982, 1983, 1992, 1993, 2002, 2003, 2009, 2010.
Years of low unemployment = 1988, 1989, 1999, 2000, 2006, 2007.

Appendix D. A search-matching model with endogenous separations and match-specific productivity

This Appendix sets up a model with endogenous separations and match-specific productivity. The main reference is Pissarides (2000), but I deviate from his model by allowing the level of match-specific productivity to follow an AR(1) process instead of a jump process with a fixed arrival rate. Appendix G below extends this model to the case of heterogeneity in worker types (indexed by i) who potentially differ in their market productivity a_i and other parameters. I assume that there is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function:

$$M = \kappa u^{\eta} v^{1-\eta}. \tag{4}$$

The job finding probability is $p(\theta) = \frac{M}{u}$ and the hiring rate $q(\theta) = \frac{M}{v}$.

Match productivity is defined as zx where z is aggregate productivity and x match-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 is

$$U(Z) = b + \beta E\left[(1 - f(\theta))U(Z') + f(\theta)W(Z', \bar{x}) \middle| Z\right], \tag{5}$$

where $Z = [z, \lambda, \sigma_\varepsilon]$ is the aggregate state, z is aggregate productivity, λ is a firm death shock, which affects all matches the same way and is independent of x, and σ_ε is the dispersion of match-specific productivity shocks. The value of being unemployed depends on the flow-value of unemployment b and the discounted value of remaining unemployed or having a job with the value $W(Z', \bar{x})$ in the next period. The value function of an employed worker is:

$$W(Z, x) = w(Z, x) + \beta E\left[(1 - \lambda)\max\{W(Z', x'), U(Z')\} + \lambda U(Z') \middle| Z, x\right], \tag{6}$$

where $w(Z, x)$ is the wage. Whenever the value of the job W is lower than the value of being unemployed U, the worker will separate and thus receive the value U in the next period. The value of posting a vacancy is:

$$V(Z) = -c + \beta E\left[(1 - q(\theta))V(Z') + q(\theta)J(Z', \bar{x}) \middle| Z\right], \tag{7}$$

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

$$J(Z,x) = zx - w(Z,x) + \beta E\left[(1-\lambda)\max\left\{J(Z',x'),V(Z')\right\} + \lambda V(Z')\right| Z,x\right]. \quad (8)$$

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

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

$$w(Z,x) = \arg\max_{w} \left[(W(Z,x) - U(Z))^{\alpha}(J(Z,x) - V(Z))^{1-\alpha}\right], \quad (9)$$

where α is the bargaining share of the worker, and separations occur whenever the joint match surplus ($S(Z,x) = W(Z,x) - U(Z) + J(Z,x) - V(Z)$) 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

$$S(Z,R(Z)) = 0. \quad (10)$$

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

Definition 1 *An equilibrium with Nash-bargaining is defined as the reservation match productivity $R(Z)$, the wage schedule $w(Z,x)$, the labor market tightness $\theta(Z)$, and the value functions $U(Z)$, $W(Z,x)$, $V(Z)$ and $J(Z,x)$, that satisfy the Nash-bargaining solution (9), the efficient-separation condition (10), the zero-profit condition $V(Z) = 0$, and the value functions (5)-(8).*

D.1 Robustness checks for baseline model

Section 4.1 in the paper explains in detail the calibration strategy and main results of the model. Table D.1 in this Appendix shows the results of the simulations of the benchmark model as well as various robustness checks, where I vary the flow value of unemployment b, the auto-correlation coefficient ρ_x, the worker's bargaining share α and various combinations. Note that, as explained in the paper, the standard deviation of match-specific shocks σ_ε and the vacancy-posting cost c are internally calibrated by matching the average separation rate (0.011) and the average job finding rate (0.31) in the merged CPS ORG data. Therefore, the values of these two parameters differ across the different calibrations of the model in Table D.1 (see at the bottom of each panel for their values).

In the simulations of the baseline model, shown in Panel A.1 in Table D.1, the cyclicality of the pre-displacement wage is an order of magnitude below the one in the data, even when compared to the residualized pre-displacement wage. The main reasons for this are twofold: First, the model generates little wage dispersion and thus shifts between high- and low-wage workers produces only small changes in terms of changes in the pre-displacement wage. Second, the ratio of the cyclicality of separations for low- to high-wage workers is only 0.73 compared to 0.46 in the merged CPS ORG data.

It is important to check the robustness of these results to calibrations of the model that allow for more wage dispersion. Panel A.3 shows the results for a calibration where the flow value of unemployment b is set to 0.4 instead of 0.71. This calibration produces more wage dispersion as shown by the differences in the pre-displacement wage reported in the table. The cyclicality of the pre-displacement wage, however, increases only slightly to 0.09, which is still far below the 2.77 for the raw wage or the 0.75 for the residual wage in the merged CPS ORG data. The main reason for this result is that, while the model does produce more wage dispersion, it is still small compared to the wage dispersion in the data, even when looking at residualized wages. The difference in the residualized average pre-displacement rate between low- and high-wage workers is around 0.55 log points in the data compared to 0.09 log point in the calibration of the model where b is set to 0.4. Moreover, the cyclicality of separations for high-wage workers relative to the cyclicality of separations for low-wage workers actually declines in this calibration as well as other calibrations that produce more wage dispersion: E.g., panels A.5, B.1, B.2, and B.3 vary parameters b and α, but the cyclicality of the pre-displacement wage remains less than 0.1. Finally, panels B.4 and B.5 show that the results are not affected by calibrations that allow for a shorter length of recessions and a longer length of expansions. Overall, I conclude that the model with match-specific productivity and endogenous separations has little promise in matching the magnitude of the compositional shifts in terms of the pre-displacement wage.

D.2 Extension with firm and establishment death

A further reason for the higher cyclicality of separations of high-wage workers may be that separations in recessions are driven by the death of firms and establishments. Establishment death will increase separations for workers of all types by the same absolute number, but more in percentage terms for those with high average separation rates (i.e., low-wage workers). A simple way of modeling such shocks is to introduce an exogenous separation shock λ, which affects all matches independently of x. Consistent with the Business Dynamics Statistics (BDS) from the Census, I set the monthly rate of establishment death λ to 0.49% in recessions and to 0.41% in expansions (see Appendix Table G.6 for details). The results in Panel A.1 of Table D.2 show that establishment death does not improve the performance of the model, mainly because the model generates little wage dispersion and because establishment death is overall important but not very cyclical.

Table D.2 also contains various robustness checks for the model with cyclical firm and establishment death. As mentioned in the paper, consistent with the Business Dynamics Statistics

(BDS) from the Census, I set the monthly rate of establishment death λ to 0.49% in recessions and to 0.41% in expansions (see Appendix Table G.6 for details). The table shows that the model generates small shifts towards high-wage workers in recessions for all calibrations. The cyclicality of the pre-displacement wage is somewhat larger for calibrations that allow for more dispersion in wages by setting a lower value for b or a higher value for α (see Panels A.3 and B.1), but the cyclicality remains below a value of 0.4, which is far below the 2.77 in the CPS ORG data for the raw wage and the 0.75 for the residual wage. Panels B.2 and B.3 also show the results for alternative sources for the calibration of the values of λ, such as the Business Employment Dynamics and Mass Layoff Statistics from the BLS, but the cyclicality of the pre-displacement wage remains far below the one in the data.

D.3 Robustness checks for model with cyclical productivity dispersion

Table D.3 contains various robustness check for the model with cyclical productivity dispersion. As mentioned in the paper, 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. This matches the evidence in Kehrig (2015) who shows that the cross-sectional dispersion in firm productivity has a cyclical standard deviation of about 5 percent (see Table 1 in his paper). The baseline version of this model produces a cyclicality of the pre-displacement wage of 0.31 and thus has some promise in explaining at least part of the patterns in the data. Interestingly, the coefficient of 0.3 for the baseline calibration of this model is very close to the cyclicality of the purely transitory effect in the NLSY79 data (0.38). The quantitative performance of the model improves further for calibrations that allow for more dispersion in wages by setting a lower value for b or a higher value for α (see Panels A.3 and B.1), with a cyclicality of about 0.7, which is still far below the cyclicality of 2.77 in the CPS ORG data for the raw wage but close to the cyclicality of the residual pre-displacement wage of 0.75. Overall, I conclude that this model may explain a part of the patterns in the data. At the same time, Kehrig also shows that the cross-sectional productivity dispersion spiked up sharply in the Great Recession, but as Figure 3 in the paper shows, the compositional shifts among the unemployed were not unusually strong over that period.

D.4 Extension where variance of match-specific productivity shocks is increasing in the level of match-specific productivity x

Table D.4 shows results where the variance of match-specific productivity shocks, σ_ε, is increasing in the level of match-specific productivity x. Panels A.1 and A.4 of Table D.4 shows the simulation results for calibrations, where σ_ε does not depend on x. Panel A.2, A.3, A.5 and A.6 show results where the standard deviation of match-specific productivity shocks is linearly increasing in x, i.e. $\sigma_\varepsilon(x) = (1 - w(x))\sigma_\varepsilon(x_{\min}) + w(x)\sigma_\varepsilon(x_{\max})$, where $w(x) = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$ and $x_{\min}$ and $x_{\max}$ are the bottom and the top for the support chosen in the discretization of the state space. $\sigma_\varepsilon(x_{\min})$ is the standard deviation of match-specific shocks at the bottom of the support of x. $\sigma_\varepsilon(x_{\min})$ is calibrated internally and set to match the average separation rate in the matched CPS ORG data (0.011). $\sigma_\varepsilon(x_{\max})$ is the standard deviation of match-specific shocks at the top of the support for x. $\sigma_\varepsilon(x_{\max})$ is calibrated and set to $3\sigma_\varepsilon(x_{\min})$ for the simulations reported in Panels A.2 and A.5 in Table D.4 and set to $7\sigma_\varepsilon(x_{\min})$ for the simulations shown in Panels A.3 and A.6. Of course, the increase of $\sigma_\varepsilon(x)$ over the relevant support of x could be fairly small, if an extremely wide support for x was chosen, but the results at the bottom of the Table show that $\sigma_\varepsilon(x)$ increases substantially between the (steady state) reservation match-productivity R to the 95th percentile of the steady state distribution of x: In Panels A.2 and A.5, $\sigma_\varepsilon(x)$ increases by about 55 percent and, in Panels A.3 and A.6, $\sigma_\varepsilon(x)$ nearly triples over this relevant range of x.

Despite the rather extreme assumptions in the calibrations shown in Panels A.3 and A.6, the cyclicality of the pre-displacement wage is nearly unaffected when compared to the results of the baseline calibrations in Panels A.1 and A.4, showing that this extension cannot account for the main fact in the paper. While the extension tends to increase the volatility of the level of separations for workers above the median wage, it also increases the average separation rate for these workers, so that the differences in the cyclicality of log separations for low- and high-wage workers are nearly unaffected. To conclude, this extension does not improve on the baseline model with match-specific productivity shocks discussed in Section D.1, as it predicts a cyclicality of the pre-displacement wage of about 0.1 compared to 2.77 in the matched CPS ORG data.

TABLE D.1 ROBUSTNESS CHECKS OF THE MAIN RESULTS OF THE BASELINE MODEL

Statistic:	***A.1*** *Baseline (b=0.71)*		***A.2*** *b=0.9*		***A.3*** *b=0.4*		***A.4*** $\rho_x = 0.90$		***A.5*** $\alpha = 0.25$, $b = 0.71$	
Cyclicality of aggregate										
… log pre-displacement wage	0.08		0.02		0.09		0.08		0.05	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.74	1.06	0.74	1.07	0.81	1.02	0.71	0.81	0.73	0.98
… log job finding rates	-0.43	-0.43	-0.37	-0.37	-0.59	-0.59	-0.41	-0.41	-0.48	-0.48
… log unemployment rates	0.96	1.26	0.96	1.26	0.98	1.11	0.97	1.06	0.97	1.16
… log reservation productivities	0.03	0.03	0.01	0.01	0.04	0.04	0.05	0.05	0.06	0.06
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.018	0.003	0.019	0.004	0.018	0.003	0.013	0.009	0.018	0.003
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.057	0.008	0.062	0.009	0.059	0.008	0.045	0.023	0.058	0.008
… log wages	0.01	0.08	0.00	0.02	0.03	0.16	-0.03	0.06	0.04	0.11
… log pre-displacement wages	0.00	0.05	0.00	0.01	0.02	0.11	-0.03	0.05	0.04	0.08
Aggregate time-series statistics:										
Std(log separation rate)	0.066		0.229		0.038		0.074		0.051	
Std(log job finding rate)	0.033		0.079		0.027		0.038		0.032	
Std(log unemployment rate)	0.054		0.192		0.025		0.070		0.040	
Internally calibrated parameters:										
σ_ε	0.023		0.007		0.046		0.056		0.044	
c	0.29		0.08		0.57		0.25		0.84	

Statistic:	***B.1*** $\alpha = 0.75$, $b = 0.71$		***B.2*** $\alpha = 0.25$, $b = 0.40$		***B.3*** $\alpha = 0.75$, $b = 0.40$		***B.4*** $\pi_{bg}=1/11.1$, $\pi_{gb}=1/59.5$, $b = 0.71$		***B.5*** $\pi_{bg}=1/11.1$, $\pi_{gb}=1/59.5$, $b = 0.40$	
Cyclicality of aggregate										
… log pre-displacement wage	0.07		0.05		0.05		0.07		0.07	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.76	1.09	0.91	0.89	0.73	0.96	0.80	1.06	0.69	0.98
… log job finding rates	-0.43	-0.43	-0.64	-0.64	-0.63	-0.63	-0.39	-0.39	-0.44	-0.44
… log unemployment rates	0.96	1.29	0.98	1.06	0.99	1.09	0.96	1.22	0.96	1.22
… log reservation productivities	0.02	0.02	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.018	0.003	0.018	0.003	0.018	0.003	0.018	0.003	0.019	0.003
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.32	0.31	0.31
… unemployment rates	0.057	0.008	0.059	0.008	0.058	0.008	0.056	0.007	0.059	0.008
… log wages	0.00	0.06	0.14	0.30	0.00	0.15	0.02	0.09	0.01	0.08
… log pre-displacement wages	-0.01	0.04	0.13	0.23	-0.01	0.09	0.02	0.07	0.01	0.05
Aggregate time-series statistics:										
Std(log separation rate)	0.089		0.034		0.036		0.056		0.141	
Std(log job finding rate)	0.039		0.026		0.028		0.030		0.061	
Std(log unemployment rate)	0.071		0.020		0.025		0.043		0.121	
Internally calibrated parameters:										
σ_ε	0.014		0.100		0.034		0.023		0.023	
c	0.09		2.00		0.21		0.30		0.28	

Notes: 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 and the cyclicality is measured in the same way as in the empirical analysis (see the notes of Table 1 and 2). Sample size for model simulations: 100,000 individuals for 2400 months.

TABLE D.2 ROBUSTNESS CHECKS OF THE MAIN RESULTS OF MODEL WITH FIRM DEATH SHOCKS

Statistic:	***A.1*** *Baseline (b=0.71)*		***A.2*** *b=0.9*		***A.3*** *b=0.4*		***A.4*** $\rho_x = 0.90$		***A.5*** $\alpha = 0.75$, $b = 0.71$	
Cyclicality of aggregate										
… log pre-displacement wage	0.04		-0.02		0.35		0.08		0.03	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.78	0.95	0.83	0.64	0.69	1.27	0.72	0.85	0.79	0.94
… log job finding rates	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34	-0.33	-0.33
… log unemployment rates	0.98	1.06	1.08	0.76	0.85	1.42	0.96	1.06	0.98	1.04
… log reservation productivities	0.02	0.02	0.01	0.01	0.02	0.02	0.04	0.04	0.01	0.01
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.016	0.006	0.016	0.006	0.016	0.006	0.013	0.009	0.016	0.006
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.051	0.018	0.051	0.018	0.050	0.017	0.041	0.026	0.050	0.017
… log wages	-0.01	0.02	0.00	0.01	-0.02	0.06	-0.03	0.05	-0.01	0.03
… log pre-displacement wages	-0.02	0.02	0.00	0.01	-0.03	0.06	-0.04	0.04	-0.01	0.03
Aggregate time-series statistics:										
Std(log separation rate)	0.096		0.260		0.052		0.078		0.096	
Std(log job finding rate)	0.038		0.091		0.028		0.037		0.037	
Std(log unemployment rate)	0.087		0.244		0.045		0.080		0.083	
Internally calibrated parameters:										
σ_ε	0.012		0.004		0.028		0.048		0.009	
c	0.24		0.07		0.55		0.26		0.09	

Statistic:	***B.1*** $\alpha = 0.75$, $b = 0.40$		***B.2*** *λ shocks calibrated to BED data*		***B.3*** *λ shocks calibrated to mass layoff data*		***B.4*** $\pi_{bg}=1/11.1$, $\pi_{gb}=1/59.5$		***B.5*** *No productivity shocks*	
Cyclicality of aggregate										
… log pre-displacement wage	0.39		0.05		0.30		0.03		0.33	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.69	1.29	0.76	0.90	0.69	1.74	0.83	1.01	0.80	1.70
… log job finding rates	-0.33	-0.33	-0.36	-0.36	-0.26	-0.26	-0.32	-0.32	-0.27	-0.27
… log unemployment rates	0.85	1.42	0.97	1.05	0.82	1.90	0.99	1.05	0.74	1.79
… log reservation productivities	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.02	0.00	0.00
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.016	0.006	0.016	0.006	0.017	0.004	0.015	0.006	0.016	0.006
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.32	0.32	0.31	0.31
… unemployment rates	0.051	0.017	0.049	0.017	0.053	0.011	0.048	0.016	0.049	0.017
… log wages	-0.02	0.07	-0.01	0.03	0.00	0.05	0.00	0.04	-0.01	0.03
… log pre-displacement wages	-0.03	0.07	-0.01	0.03	0.00	0.04	0.00	0.04	-0.01	0.03
Aggregate time-series statistics:										
Std(log separation rate)	0.052		0.072		0.123		0.075		0.041	
Std(log job finding rate)	0.027		0.034		0.037		0.031		0.025	
Std(log unemployment rate)	0.044		0.065		0.103		0.059		0.028	
Internally calibrated parameters:										
σ_ε	0.020		0.013		0.016		0.013		0.013	
c	0.19		0.26		0.25		0.27		0.26	

Notes: 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 and the cyclicality is measured in the same way as in the empirical analysis (see the notes of Table 1 and 2). Sample size for model simulations: 100,000 individuals for 2400 months.

TABLE D.3 ROBUSTNESS CHECKS OF THE MAIN RESULTS OF MODEL WITH DISPERSION SHOCKS

Statistic:	***A.1*** *Baseline (b=0.71)*		***A.2*** *b=0.9*		***A.3*** *b=0.4*		***A.4*** $\rho_x = 0.90$		***A.5*** $\alpha = 0.75$, $b = 0.71$	
Cyclicality of aggregate										
… log pre-displacement wage	0.31		0.01		0.68		0.24		0.24	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.73	1.80	0.52	0.74	0.92	2.09	0.82	1.07	0.72	1.61
… log job finding rates	-0.23	-0.23	-0.61	-0.61	-0.12	-0.12	-0.18	-0.18	-0.25	-0.25
… log unemployment rates	0.87	2.00	0.94	1.13	0.85	2.18	0.90	1.20	0.88	1.82
… log reservation productivities	0.00	0.00	0.01	0.01	-0.03	-0.03	0.00	0.00	0.00	0.00
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.018	0.003	0.047	0.013	0.018	0.003	0.013	0.008	0.019	0.003
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.056	0.007	0.138	0.033	0.058	0.008	0.043	0.022	0.059	0.008
… log wages	0.01	0.07	0.02	0.06	0.03	0.16	-0.02	0.06	0.00	0.07
… log pre-displacement wages	0.00	0.05	0.02	0.04	0.02	0.11	-0.03	0.05	0.00	0.04
Aggregate time-series statistics:										
Std(log separation rate)	0.085		0.181		0.084		0.137		0.096	
Std(log job finding rate)	0.033		0.156		0.027		0.036		0.035	
Std(log unemployment rate)	0.085		0.246		0.062		0.137		0.100	
Internally calibrated parameters:										
σ_ε	0.021		0.013		0.044		0.053		0.014	
c	0.28		0.03		0.57		0.25		0.09	

Statistic:	***B.1*** $\alpha = 0.75$, $b = 0.40$		***B.2*** *Smaller dispersion shocks (std = 2.5%)*		***B.3*** $\pi_{bg}=1/11.1$, $\pi_{gb}=1/59.5$, $b = 0.71$		***B.4*** $z_b=0.95$, $z_g=1.05$, $b = 0.71$		***B.5*** $z_b=0.95$, $z_g=1.05$, $b = 0.40$	
Cyclicality of aggregate										
… log pre-displacement wage	0.72		0.22		0.27		0.19		0.56	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.86	2.04	0.68	1.41	0.76	1.68	0.66	1.32	0.69	1.66
… log job finding rates	-0.15	-0.15	-0.32	-0.32	-0.22	-0.22	-0.33	-0.33	-0.28	-0.28
… log unemployment rates	0.84	2.14	0.90	1.62	0.88	1.84	0.91	1.56	0.88	1.87
… log reservation productivities	-0.02	-0.02	0.01	0.01	0.00	0.00	0.01	0.01	-0.01	-0.01
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.019	0.004	0.018	0.003	0.018	0.003	0.018	0.003	0.018	0.003
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.060	0.008	0.057	0.008	0.055	0.007	0.059	0.008	0.057	0.007
… log wages	0.01	0.16	0.01	0.08	0.02	0.09	0.01	0.08	0.03	0.16
… log pre-displacement wages	-0.01	0.10	0.01	0.06	0.02	0.06	0.01	0.06	0.02	0.11
Aggregate time-series statistics:										
Std(log separation rate)	0.080		0.062		0.069		0.141		0.083	
Std(log job finding rate)	0.026		0.032		0.030		0.059		0.037	
Std(log unemployment rate)	0.063		0.065		0.066		0.157		0.087	
Internally calibrated parameters:										
σ_ε	0.034		0.023		0.022		0.023		0.043	
c	0.21		0.30		0.29		0.28		0.56	

Notes: 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 and the cyclicality is measured in the same way as in the empirical analysis (see the notes of Table 1 and 2). Sample size for model simulations: 100,000 individuals for 2400 months.

TABLE D.4 MODEL WHERE VARIANCE OF MATCH-SPECIFIC PRODUCTIVITY SHOCKS IS INCREASING IN THE LEVEL OF MATCH-SPECIFIC PRODUCTIVITY X

Statistic:	***A.1*** *Baseline (b=0.71)*		***A.2*** $\sigma_\varepsilon(x_{min})/\sigma_\varepsilon(x_{max}) = 3$ *b=0.71*		***A.3*** $\sigma_\varepsilon(x_{min})/\sigma_\varepsilon(x_{max}) = 7$ *b=0.71*		***A.4*** *Same as baseline but with b=0.4*		***A.5*** $\sigma_\varepsilon(x_{min})/\sigma_\varepsilon(x_{max}) = 3$ *b=0.4*		***A.6*** $\sigma_\varepsilon(x_{min})/\sigma_\varepsilon(x_{max}) = 7$ *b=0.4*	
Cyclicality of aggregate												
… log pre-displacement wage	0.08		0.06		0.07		0.09		0.11		0.10	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.74	1.06	0.81	1.12	0.86	1.15	0.81	1.02	0.76	0.97	0.86	1.01
… log job finding rates	-0.43	-0.43	-0.35	-0.35	-0.27	-0.27	-0.59	-0.59	-0.56	-0.56	-0.43	-0.43
… log unemployment rates	0.96	1.26	0.96	1.26	0.95	1.25	0.98	1.11	0.98	1.17	0.97	1.16
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.018	0.003	0.019	0.004	0.017	0.005	0.018	0.003	0.018	0.004	0.017	0.005
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.057	0.008	0.059	0.009	0.055	0.012	0.059	0.008	0.059	0.009	0.057	0.012
… log wages	0.01	0.08	0.00	0.06	-0.02	0.02	0.03	0.16	0.01	0.13	-0.05	0.05
… log pre-displacement wages	0.00	0.05	0.00	0.04	-0.02	0.01	0.02	0.11	0.00	0.08	-0.05	0.02
Aggregate time-series statistics:												
Std(log separation rate)	0.066		0.084		0.118		0.038		0.040		0.047	
Std(log job finding rate)	0.033		0.034		0.036		0.027		0.028		0.027	
Std(log unemployment rate)	0.054		0.064		0.092		0.025		0.030		0.033	
Internally calibrated parameters:												
σ_ε (at x=R)	**0.023**		**0.016**		**0.010**		**0.046**		**0.033**		**0.022**	
σ_ε (at x=95th percentile)	**0.023**		**0.025**		**0.029**		**0.046**		**0.051**		**0.064**	
c	0.29		0.26		0.25		0.57		0.55		0.56	

Notes: 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 and the cyclicality is measured in the same way as in the empirical analysis (see the notes of Table 1 and 2). The value of the standard deviation of match-specific productivity shocks, σ_ε, is shown at the (steady-state) reservation match productivity R as well as the 95th percentile of the steady-state distribution of x. Sample size for model simulations: 100,000 individuals for 2400 months.

Appendix E. A Search-matching model with endogenous separations, match-specific productivity and staggered Nash wage bargaining

This appendix sets up a model with staggered Nash wage bargaining and endogenous separations. As can be seen from the value functions further below, the basic notation and setup of the model is the same as for the baseline model in the paper. In particular, the process of matching workers and firms (including the matching function) and the process of aggregate and match-specific productivity are identical in the baseline model and thus I do not describe these processes in this Appendix. The model here differs in two important dimensions from the baseline model in Appendix D:

1. *Staggered Nash wage bargaining*: I assume that workers and firms bargain wages at the beginning of the employment relationship according to the Nash-bargaining rule. Once the match is formed, wages are renegotiated according to the Nash-bargaining rule with probability τ, and thus wages are not adjusted with probability $(1-\tau)$. While the set up of wage rigidity in the model is inspired by Gertler and Trigari (2009), it differs from their work in important dimensions. Most importantly, Gertler and Trigari focus their attention on the effect of wage rigidity on the hiring margin and thus assume exogenous separations, whereas my model allows for match-specific productivity and endogenous separations.

2. *Wage rigidity and inefficient separations*: When wages cannot be reset in a given period, I assume that wages are completely rigid and do not adjust even if it implies inefficient separation. More precisely, I assume that worker-firm matches dissolve whenever the share of the surplus for either the worker or the firm is negative, and thus it may dissolve even if the joint surplus is positive. Separations, therefore, may be inefficient in cases where the wage cannot be reset and either match-specific productivity x or aggregate productivity z changes. The reason is that in both cases the sticky wage may no longer be in the new bargaining set, which is determined by the new x and/or the new z.

E.1 Value functions, wage setting and equilibrium

The value function of the unemployed worker is:

$$U\left(z\right) = b + \beta E\left[(1-f(\theta))U(z') + f(\theta)W(z', \bar{x}, w^{NB}(z', \bar{x}))\middle| Z\right] \tag{11}$$

where b is the flow value of unemployment, $f(.)$ is the job-finding rate, θ is the labor market tightness, z is aggregate labor market productivity, $\overline{x}$ is median match-specific productivity and

$w^{NB}(z,x)$ is the Nash-bargained wage in state z and x.[14]

The value function of the employed worker is:

$$\begin{aligned} W(z,x,w) &= w + \beta E[(1-\tau)(1-\lambda^f(z',x',w))\max\{W(z',x',w),U(z')\} \\ &\quad +(1-\tau)\lambda^f(z',x',w)U(z') \\ &\quad +\tau\max\left\{W(z',x',w^{NB}(z',x')),U(z')\right\}\big|\, z,x] \end{aligned} \tag{12}$$

where τ is the probability of a Calvo-type Fairy visiting the match and allowing for wages to be re-bargained. Note that the wage in this model is a state variable, as it cannot be freely reset every period and thus persists over time. $\lambda^f(z,x,w)$ is an indicator function for whether the firm fires the worker in state (z,x,w). More precisely,

$$\lambda^f(z,x,w) = \begin{cases} 1 & \text{if } J(z,x,w) - V(z) < 0 \\ 0 & \text{if } J(z,x,w) - V(z) \geq 0 \end{cases}.$$

The value function of the vacant firm is:

$$V(z) = -c + \beta E[(1-q(\theta))V(z') + q(\theta)J(z',\bar{x}))|\, z] \tag{13}$$

where c is the vacancy posting cost and $q(.)$ is the job-filling rate.

The value function of the matched firms is:

$$\begin{aligned} J(z,x,w) &= zx - w + \beta E[(1-\tau)(1-\lambda^q(z',x',w))\max\{J(z',x',w),V(z')\} \\ &\quad +(1-\tau)\lambda^q(z',x',w)V(z') \\ &\quad +\tau\max\left\{J(z',x',w^{NB}(z',x')),V(z')\right\}\big|\, z,x] \end{aligned} \tag{14}$$

where zx is the output of the match and $\lambda^q(z,x,w)$ is an indicator function for whether the worker quits in state (z,x,w). More precisely,

$$\lambda^q(z,x,w) = \begin{cases} 1 & \text{if } W(z,x,w) - U(z) < 0 \\ 0 & \text{if } W(z,x,w) - U(z) \geq 0 \end{cases}.$$

Separations occur whenever the share of the surplus appropriated by either the worker or the firm is negative, and thus the reservation match-specific productivities, i.e. the level of

[14] Equations (11) and (13) 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 Appendix.

match-specific productivity x below which the worker quits or the firm fires the worker, satisfy:

$$W(z, R^w(z,w), w) - U(z) = 0, \tag{15}$$

$$J(z, R^f(z,w), w) - V(z) = 0. \tag{16}$$

In periods where the wage can be reset, it is assumed to satisfy the Nash-bargaining solution

$$w^{NB}(z,x) = \arg\max_w \left[W(z,x,w) - U(z)\right]^{\alpha} \left[J(z,x,w) - V(z)\right]^{1-\alpha}. \tag{17}$$

Definition 2 *The search-matching model with staggered nash wage bargaining and endogenous separations is defined as the worker's reservation productivity threshold $R^w(z,w)$, the firm's reservation productivity threshold $R^f(z,w)$, the wage schedule $w^{NB}(z,x)$, the labor market tightness $\theta(z)$, and the value functions $U(z)$, $W(z,x,w)$, $V(z)$ and $J(z,x,w)$, that satisfy the worker-separation condition (15), the firm-separation condition (16), the Nash-bargaining solution (17), the zero-profit condition $V(z) = 0$, and the value functions (11)-(14).*

Note that in the case where the wage can be renegotiated, the reservation match productivities are independent of the wage and the match is dissolved only if the joint surplus is negative, and thus the efficient-separation match productivity in this case is $R(z) = R^w(z,w) = R^f(z,w)$.

Proposition 3 *If $\sigma_\varepsilon > 0$, then the search-matching model with wage rigidity above features weakly inefficient separations.*

Proof. Consider the case where $J(z,x,w^{NB}(z,x)) = 0$, i.e. match-specific productivity x is just high enough to sustain a zero value of the filled job if wages are Nash-bargained (i.e., $x = R(z)$). The upper bound on the wage bargaining set, denoted $\tilde{w}(z,x)$ and determined by the condition $J(z,x,\tilde{w}(z,x)) = 0$, is then equal to Nash-bargained wage, i.e. $w^{NB}(z,x) = \tilde{w}(z,x)$.

In the presence of wage rigidity, higher x increases the value of being employed at a given wage, $W(z,x,w)$, because of the persistence in x, implying that workers will get paid higher wages in the future when they are allowed to rebargain the wage. In the presence of wage rigidity, higher x increases the value of a filled job for the firm at a given wage, $J(z,x,w)$, because it increases the firm's output relative to its labor cost. Given that higher x increases the value of the employment relationship for both workers and firms, this implies that the Nash-bargained wage is increasing in x.

Given that higher x increases the value of the employment relationship for both workers and firms and thus the Nash-bargained wage, then for any $\hat{x} > x = R(z)$, we get that $w^{NB}(z,\hat{x}) > \tilde{w}(z,R(z)) = w^{NB}(z,R(z))$. If match productivity falls from $\hat{x}$ to x, but wages are not allowed to adjust, this implies that $J(z,x,w^{NB}(z,\hat{x})) < 0$ and thus the firm fires the worker, even if the joint surplus is non-negative. ∎

The simulations of the model discussed further below reveal a substantial fraction of separations that are inefficient. The bottom panel of Table E. in the Appendix decomposes the average aggregate separation rate into efficient and inefficient separations, and the share of inefficient separations exceeds 50 percent for all five calibrations shown.

E.2 Calibration

Parameters are calibrated in the same way as in the baseline model in the paper, unless otherwise stated here. I calibrate τ to the frequency of wage adjustment on a given job spell as reported in the recent paper by Barattieri, Basu and Gottschalk (2014). They report a quarterly frequency of overall wage adjustment of between 21.1 and 26.6 percent, but, once restricted to the same job, the quarterly frequency reduces to between 16.3 and 21.6 percent. I focus on the lower end of this range and set the *monthly* frequency of wage adjustment τ to 0.0575, implying an average duration of a wage spell of about 18 months.

Since workers are homogenous, I can no longer follow the calibration strategy in the baseline model and choose group-specific parameters to match group-specific separation rates. Instead, I internally calibrate σ_ε to match the average (aggregate) separation rate and show the simulation results for various choices of the flow value of unemployment b.

E.3 Results and further dicussion

The results shown in Appendix Table E suggest that wage rigidity has only a very limited impact on the cyclicality of the pre-displacement wage, as the coefficient of interest shown in the top row in the table is more than an order of magnitude below the compositional shifts documented in the paper. To go in order of the Table E, the panel A.1 shows the results where I set $b = 0.71$ as in Hall and Milgrom (2008). Matching an average separation rate of 1.1% requires setting $\sigma_\varepsilon = 0.016$, a modest value. Interestingly, the average of the separation rate of those above the median wage and those below the median wage exactly matches the averages in the data. The reason for the lower rate of separation for high-wage workers is the high persistence in the process of match productivity x: high-wage workers are those who had a high x at the time the wage was set, but, because x is highly persistent, x today is likely to be close to the x at the time of the wage bargain. Therefore, high-wage workers tend to be high-x workers and thus are less likely to separate. Relaxing the persistence increases the average separation rates for high-wage workers to the point where they are on average more likely to separate than low-wage workers, as the high wage is less likely to be associated with high x and thus the reason for the firm to fire the worker (see the results in the panel A.4).

The results in Panel A.1 show that the model with wage rigidity generates small movements in the composition of the pool of unemployed that go in the same direction as documented in the data. Quantitatively, a one percentage point increase in the unemployment rate results in a 0.05 percent increase in the average log pre-displacement wage, which is tiny compared to the 2.77 percent increase in the CPS data (see Table 1). The reason for the small magnitude is two-fold: First, the differences in the cyclicality of the separation rates between those below and above the median pre-displacement wage are relatively modest and as a result the composition of inflows into the pool of unemployed does not change much. Second, overall wage dispersion in the model is modest, as the model generates a lot of inefficient separations and thus requires only a small amount of dispersion in match-productivity shocks captured by the parameter σ_ε, which, along with aggregate productivity shocks, are the only sources of wage dispersion in the model. Therefore, even if high-wage workers have more cyclical separation rates, this translates into small changes in the composition of the pool of unemployed workers.

To make sure that these results are not driven by particular calibration choices, I solve and simulate the model for other calibration choices that allow for a higher level of σ_ε and thus more dispersion in wages. To this purpose, I set the flow value of unemployment b to 0.4 and 0.9 instead of 0.71. The results in Panel A.2 of Table E show that the calibration with $b = 0.4$ requires a dispersion of match-specific productivity shocks that is $\sigma_\varepsilon = 0.035$ to match the average aggregate separation rate, but this calibration generates cyclical movements in the composition of the unemployed of similar magnitude as the baseline calibration.

Panel A.4 of Table E shows results for a model where the auto-correlation coefficient of match-productivity shocks is set to 0.9 (instead of 0.98). The value of 0.98 is taken from the paper of Bils, Chang and Kim (2012) who base their calibration of a model with flexible wages on the high-autocorrelation of wages in the data. However, in the model here, wages are more persistent due to wage rigidity and thus the underlying x may be substantially less persistent but the model may still feature highly persistent wages. The results show that the higher cyclicality of separations is not robust to this change, and the average pre-displacement wage becomes acyclical. The reason is that the *average* separation rate for high-wage workers is higher compared to low-wage workers, and thus, even if the separation rate for high-wage workers increase in recessions, the log of the separation rate may increase by the same amount or even less for high-wage workers. As shown in Section 2 of the paper, what matters for the compositional changes in the pool of the unemployed are changes of the *log* of the separation rate.

In Panel A.5 of the Table E, I allow for (counterfactually) bigger shocks in aggregate labor productivity, by setting the standard deviation of these shocks to 5 percent instead of 2 percent. The cyclicality of the pre-displacement wage again is somewhat larger but is still very small compared to the patterns in the data.

Finally, in Panel A.6, I allow for less wage rigidity by setting the *monthly* frequency of wage adjustment τ to 0.083, implying an average duration of a wage spell of 12 months instead of

18 months. The results show slightly larger shifts in the composition of the unemployed but still tiny compared to the data. The cyclicality of the pre-displacement wage is 0.06 compared to 2.77 in the CPS ORG data. Another useful comparison is the model with no wage rigidity discussed in the previous section, which yields a cyclicality of the pre-displacement wage of 0.07. This suggests that wage rigidity actually renders the performance of the model even worse compared to a model without wage rigidity.

One caveat of the model proposed here is that it imposes an exogenous probability of renegotiating the wage and thus the probability of adjusting the wage is unrelated to the size of the match surplus. As a consequence, the model generates a lot of inefficient separations. An alternative model that relates the probability of wage adjustment to the gain of the wage adjustment would generate fewer inefficient separations, as in cases where the match surplus is high enough the worker and the firm would decide to renegotiate the wage. As shown in Table E, relaxing the degree of wage rigidity slightly improves the performance of the model, but even for a model where wages are completely flexible and separations always efficient (see model B.1 in Table 4 in the paper), the cyclicality of the pre-displacement wage remains an order of magnitude below the one in the data.

One may also argue that wage rigidity is relevant in a model with ex-ante heterogeneity in worker productivity, if the frequency of wage adjustment differs across types. Note, however, that matches with high-ability types produce a larger surplus and thus the incentive of adjusting wages in the face of adverse shocks is substantially larger for these matches. This also fits the prevalence in high-skilled jobs of wage contracts with bonus pay, which is by its nature more flexible than the base wage rate. Therefore, if wages are more flexible for high-ability types, one would expect that introducing wage rigidity into the model with ex-ante heterogeneity in Appendix G would worsen the performance of the model, as it would further increase the cyclicality of separations for the low-ability types, whereas in the data separations of high-wage workers are more cyclical.

TABLE E. RESULTS FOR THE MODEL WITH WAGE RIGIDITY

Statistics:	**A.1** $b = 0.71$, $\sigma_\varepsilon = 0.016$		**A.2** $b = 0.4$, $\sigma_\varepsilon = 0.035$		**A.3** $b = 0.9$, $\sigma_\varepsilon = 0.003$		**A.4** $b = 0.71$, $\rho_x = 0.9$, $\sigma_\varepsilon = 0.045$		**A.5** $b = 0.71$, z_b=0.95, z_g=1.05, $\sigma_\varepsilon = 0.015$		**A.6** $b = 0.71$, $\tau = 0.083$, $\sigma_\varepsilon = 0.02$	
Cyclicality of aggregate												
… log pre-displacement wage	0.05		0.05		0.04		0.00		0.07		0.06	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.96	1.17	0.94	1.04	0.66	1.09	1.10	1.07	0.75	1.07	0.99	1.21
… log job finding rates	-0.13	-0.13	-0.28	-0.28	-0.17	-0.17	-0.11	-0.11	-0.20	-0.20	-0.18	-0.18
… log unemployment rates	0.94	1.15	0.97	1.09	0.85	1.37	1.02	1.01	0.88	1.26	0.95	1.16
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.014	0.008	0.015	0.008	0.012	0.007	0.010	0.013	0.018	0.010	0.018	0.008
… job finding rates	0.31	0.31	0.31	0.31	0.30	0.30	0.31	0.31	0.30	0.30	0.31	0.31
… unemployment rates	0.045	0.022	0.046	0.023	0.042	0.026	0.032	0.039	0.060	0.033	0.057	0.024
… log wages	0.01	0.04	0.03	0.10	0.00	0.00	0.00	0.02	0.01	0.04	0.02	0.06
… log pre-displacement wages	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
Aggregate time-series statistics:												
Std(log separation rate)	0.330		0.177		0.704		0.392		0.459		0.246	
Std(log job finding rate)	0.051		0.052		0.204		0.048		0.118		0.048	
Std(log unemployment rate)	0.237		0.123		0.823		0.277		0.456		0.173	
AR(1) coefficient of log wages	0.98		0.98		0.95		0.96		0.97		0.97	
Share of inefficient separations	73%		76%		59%		90%		80%		66%	

Notes: Efficient separations are defined as separations that occur when the joint match surplus is negative. Inefficient separations are defined as separations that occur when the joint match surplus is non-negative. 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: Data are simulated for a cross-section of 50,000 individuals for a period of 2400 months.

Appendix F. A model with compensating differentials for unemployment risk

This appendix sets up a stylized model of unemployment with cyclical unemployment risk. It does not model the employers' recruiting decision but instead takes as given the cyclical properties of the matching process (i.e., the cyclical properties of the job separation and job finding probability).

F.1 Value functions

There are two types of jobs, one with less unemployment risk (type $i = s$, where s stands for "safe" job) and one with more unemployment risk (type $i = r$, where r stands for "risky").

The value function of workers in job r in aggregate state z, denoted $W_r(z)$, is:

$$W_r(z) = u(w_r(z)) + \beta E\left[W_r\left(z'\right) - \lambda_r(z')(W_r(z') - U(z'))|z\right]$$

where $u(w_r(z))$ is the utility flow while in job v, $W_v\left(z'\right)$ is the future value given no job separation in the next period, $\lambda_r(z)$ is the job separation probability and $(W_r(z') - U(z'))$ is the loss in value given job separation.

The value function of workers in job s in aggregate state z, denoted $W_s(z)$, is:

$$W_s(z) = u(w_s(z)) + \beta E\left[W_s\left(z'\right) - \lambda_s(z')(W_s(z') - U(z'))|z\right]$$

where $u(w_s(z))$ is the utility flow while in job s, $W_s\left(z'\right)$ is the future value given no job separation in the next period, $\lambda_s(z)$ is the job separation probability and $(W_s(z') - U(z'))$ is the loss in value given job separation.

And the value function of the unemployed worker is:

$$U\left(z\right) = u(b) + \beta E\left[U\left(z'\right) + f(z)\pi_r(W_r\left(z'\right) - U\left(z'\right)) + f(z)(1 - \pi_r)(W_s\left(z'\right) - U\left(z'\right))|z\right]$$

where $u(b)$ is the utility flow while unemployed, $f(z)$ is the job finding probability in state z and π_r is the share of risky jobs.

The main goal of this exercise is to determine the wage premium of jobs of type r over jobs of type s. I abstract from the employer side in this model, normalize wages of safe jobs equal to one and set the wage premium of jobs of type r over jobs of type s, assuming that wages *fully* compensate for the lower continuation value of jobs of type r. To that purpose, I assume that relative wages satisfy the equation

$$W_r(z) = W_s(z),$$

which states that the value of the two types of jobs is the same in all aggregate states.[15]

F.2 Calibration

This stylized model is calibrated with two aggregate states ($z = b$(ad), g(ood)), where each state has an expected duration of two years (as for the other models in the paper). The remaining parameters of the model are calibrated as follows:

- The separation shocks are calibrated to the CPS ORG data. To that purpose, I divide my sample in the CPS ORG data into periods where the monthly aggregate unemployment rate is above its HP-trend and periods where it is below its HP-trend, and compute the average monthly separation rate for both samples for low- and high-wage workers. I directly use these values to calibrate the $\lambda_i(z)$ shocks in this calibration, i.e. I set:

$$\begin{aligned}\lambda_r(g) &= 0.0138 \\ \lambda_r(b) &= 0.0152 \\ \lambda_s(g) &= 0.0067 \\ \lambda_s(b) &= 0.0085,\end{aligned}$$

  where b stands for the bad aggregate state and g stands for the good aggregate state.

- The average job finding rate is calibrated to match 0.31 (as in the data), the cyclicality of the job finding rate is calibrated so as to much the cyclcal volatility in the data, i.e. $f(b) = 0.28$ and $f(g) = 0.34$.

- The share of jobs upon job-finding is set to $\pi_r = 0.5$, consistent with the empirical analysis, where I split the data at the median wage.

- The monthly discount factor is set to $\beta = 0.9966$ as in the baseline model in the paper.

- The wage for the job of type s, w_s, is normalized to 1 in all aggregate states.

- The unemployment benefit is set to $b = 0.8$. The implied decline of consumption for workers with jobs of type s is near the upper end of empirical measures of consumption declines upon unemployment (Gruber, 1997, finds a decline of consumption at unemployment of around 22.2 percent for workers with no unemployment insurance).

- The utility function is assumed to be of Constant Relative Risk Aversion (CRRA) form with CRRA parameter $\gamma = 3$.

[15] A version of the model where I assume instead that the two jobs yield the same value only on average (but not in all aggregate states) yields very similar results.

F.3 Results

Table F displays the results of the simulations. I compute the main statistic of interest in this calibrated version of the model, i.e. I compute the cyclicality of the average wage (from one year ago) of the unemployed ($\frac{d \ln w_t^u}{dU_t}$). The resulting regression coefficient in the model is -0.01, which is tiny and in the opposite direction of the coefficient of 2.77 in Table 1 for the matched CPS ORG sample. The reason is that the risky job is the one with the high average separation rate and thus commands a wage premium. However, as discussed in the empirical analysis, log separation rates are less cyclical for the group with high average separation rates. Therefore, the compositional shifts in the pool of unemployed are in the opposite direction of the data.

Column 3 in Table F peform additional simulations, where I assume that both types of jobs have the same average separation rate, but separations are cyclical only for the risky job. I.e., I set

$$\begin{aligned} \lambda_r(g) &= 0.009 \\ \lambda_r(b) &= 0.013 \\ \lambda_s(g) &= 0.011 \\ \lambda_s(b) &= 0.011 \end{aligned}$$

The results show compositional shifts towards high-wage jobs in recessions, but these shifts are quantitatively tiny. The coefficient on the log-predisplacement rate is less than 0.01 compared to 2.77 in the data. The main reason for this result is that the model generates hardly any wage differential between the two types of jobs. The wage premium for the job with cyclical unemployment risk is less than 1 percent, and thus the model cannot generate any meaningful compositional changes in terms of the previous wage.

Of course, the wage premium of the job with cyclical unemployment risk depends on the risk aversion parameter γ. To test the robustness of the result above, I set $\gamma = 10$ and simulate the model. The resulting wage premium (see columns 2, 4 and 5 in Table F) for the job of type r is slightly larger, but still less than 0.01. Column 5 in Table F shows results where I doubled the standard deviation of the job separation rate (for the risky job) and the job finding rate, but even under these extreme assumptions, the cyclicality of the average wage of the unemployed is less than 0.01, which is still very small compared to the coefficient of 2.77 in Table 1 for the matched CPS ORG sample.

To conclude, even though this model is very simple and does not rely on any microfoundations in the wage setting and job finding process, the results suggest that cyclical unemployment risk commands a small wage premium and thus can explain only a negligible part of the empirical patterns described in this paper. The main reason is that for realistic calibrations of the job finding and job separation rates, a small wage premium is sufficient to compensate for the cyclical separation risk. More importantly, the baseline results which rely on separation rates calibrated to the CPS ORG data predict shifts in the opposite direction of the data, because the average separation risk dominates the cyclical separation risk in terms of compensating differentials.

TABLE F. RESULTS FOR THE MODEL WITH COMPENSATING WAGE DIFFERENTIALS

Statistics:	**(1)** Baseline		**(2)** CRRA = 10		**(3)** Jobs differ only in cyclical unemployment risk		**(4)** Jobs differ only in cyclical unemployment risk, CRRA=10		**(5)** Jobs differ only in cyclical unemployment risk, CRRA=10	
Cyclicality of aggregate										
… log pre-displacement wage	-0.01		-0.03		0.00		0.00		0.01	
Cyclicality of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… log separation rates	0.68	0.28	0.68	0.28	0.00	1.02	0.00	1.01	0.00	1.14
… log job finding rates	-0.60	-0.60	-0.61	-0.61	-0.59	-0.59	-0.57	-0.57	-0.54	-0.54
… log unemployment rates	1.18	0.79	1.18	0.80	0.54	1.46	0.53	1.45	0.49	1.53
Average of group-specific	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}	w_{low}	w_{high}
… separation rates	0.008	0.015	0.008	0.015	0.011	0.011	0.011	0.011	0.011	0.012
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.024	0.044	0.025	0.044	0.035	0.037	0.034	0.034	0.035	0.039
… log wages	0.000	0.006	0.000	0.017	0.000	0.000	0.000	0.000	0.000	0.004
Aggregate time-series statistics:										
Std(log separation rate)	0.063		0.060		0.076		0.078		0.223	
Std(log job finding rate)	0.084		0.081		0.080		0.083		0.205	
Std(log unemployment rate)	0.131		0.123		0.128		0.137		0.357	

Notes: 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 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.

Appendix G. A search-matching model with endogenous separations, match-specific productivity and ex-ante worker heterogeneity

This Appendix extends the model of Appendix D to the case of heterogeneity in worker types (indexed by i) who potentially differ in their market productivity a_i and 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.[16] More precisely, there is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function:

$$M_i = \kappa_i u_i^{\eta} v_i^{1-\eta}. \tag{18}$$

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:

$$U_i(Z) = b_i + \beta E\left[(1 - f(\theta_i))U_i(Z') + f(\theta_i)W_i(Z', \bar{x}) \middle| Z\right], \tag{19}$$

where $Z = [z, \lambda, \sigma_\varepsilon]$ is the aggregate state, z is aggregate productivity, λ is a firm death shock, which affects all matches the same way and is independent of x, and σ_ε is the dispersion of match-specific productivity shocks. 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 $W_i(Z', \bar{x})$ in the next period. The value function of an employed worker of type i is:

$$W_i(Z, x) = w_i(Z, x) + \beta E\left[(1 - \lambda)\max\left\{W_i(Z', x'), U_i(Z')\right\} + \lambda U_i(Z') \middle| Z, x\right], \tag{20}$$

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 a vacancy of a firm searching for a worker of type i is:

$$V_i(Z) = -c_i + \beta E\left[(1 - q(\theta_i))V_i(Z') + q(\theta_i)J_i(Z', \bar{x}) \middle| Z\right], \tag{21}$$

which depends on the vacancy posting cost c_i and the discounted future expected value. The

[16] The Appendix I.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.

value of a vacancy filled with a worker of type i is:

$$J_i(Z,x) = zxa_i - w_i(Z,x) + \beta E\left[(1-\lambda)\max\left\{J_i(Z',x'), V_i(Z')\right\} + \lambda V_i(Z')\middle|\, Z, x\right]. \tag{22}$$

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:

$$w_i(Z,x) = \arg\max_{w_i}\left[(W_i(Z,x) - U_i(Z))^{\alpha}(J_i(Z,x) - V_i(Z))^{1-\alpha}\right], \tag{23}$$

where α 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

$$S_i(Z, R_i(Z)) = 0. \tag{24}$$

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

Definition 4 *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 (23), the efficient-separation condition (24), the zero-profit condition $V_i(Z) = 0$, and the value functions (19)-(22).*

G.1 The relationship between the distribution of match-specific productivity and the separation rate

This section provides additional details on the baseline model in the paper, and in particular, on the main result of the baseline calibration that separations are more cyclical for low-ability types.

The separation rate of group i at any point depends on the distribution of match-specific productivity. The separation rate of group i can be written as:

$$s_i = \int F_{\varepsilon}(R_i|x_{-1})g_i(x_{-1})dx_{-1},$$

where F_{ε} is the cumulative density function of the innovation term in the law of motion of x (time subscripts t are dropped here for convenience). In the case of log normally distributed innovations, then $f_{\varepsilon}(R_i|x_{-1}) = \phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_{\varepsilon})$ and $F_{\varepsilon}(R_i|x_{-1}) = \Phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_{\varepsilon})$, where $\phi(k, \mu, \sigma)$ and $\Phi(k, \mu, \sigma)$ are the normal pdf and the normal cdf with mean μ and standard deviation σ evaluated at k. The elasticity of separations to productivity shocks (on impact) then can be written as:

$$\frac{d \ln s_i}{d \ln z} = \widetilde{M_i} \frac{d \ln R_i}{d \ln z}, \tag{25}$$

where

$$\widetilde{M_i} = \frac{\displaystyle\int \phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_\varepsilon) g_i(x_{-1}) dx_{-1}}{\displaystyle\int \Phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_\varepsilon) g_i(x_{-1}) dx_{t-1}}.$$

It is clear from equation (25) that the elasticity of separations depends on two main elements:

1. A weighted average of the density of the innovation term ε at the reservation productivity threshold R_i, divided by the separation rate $s_i = \displaystyle\int \Phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_\varepsilon) g_i(x_{t-1}) dx_{t-1}$.
2. The response of the reservation match productivity threshold R_i to aggregate productivity shocks.

It follows that even if $\frac{d \ln R_i}{d \ln z}$ is the same across groups, separations may be more cyclical for groups with a higher density g of match productivities x_{-1} near the threshold R_i. Moreover, the density $\phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_\varepsilon)$ relative to the cumulative density $\Phi(\ln R_i, \rho_x \ln x_{-1}, \sigma_\varepsilon)$ may depend on the level of R_i and thus affect the cyclicality of separations for groups with differences in the average level of R_i.

To gain some intuition on the importance of these issues for the cyclicality of separations, it is useful to consider the special case where match productivities are serially uncorrelated. In this case, one can write:

$$\frac{d \ln s_i}{d \ln z} = \frac{\phi(\ln R_i, 0, \sigma_\varepsilon)}{\Phi(\ln R_i, 0, \sigma_\varepsilon)} \frac{d \ln R_i}{d \ln z},$$

where $M_i = \frac{\phi(\ln R_i, 0, \sigma_\varepsilon)}{\Phi(\ln R_i, 0, \sigma_\varepsilon)}$ is the inverse Mills ratio for the distribution of match productivity draws $\ln x = \varepsilon$. Note that for the (log) normal distribution, the inverse Mills ratio is decreasing in R_i, and thus, the cyclicality of the separation rate is decreasing in the level of R_i even if $\frac{d \ln R_i}{d \ln z}$ is the same across groups. Therefore, high-ability types may have more cyclical separations than low-ability types simply because the Mills ratio is higher at a lower level of R_i. Differences in the inverse Mills ratio between high- and low-ability types are restricted, however, by the calibration strategy that aims at matching the average separation rate for high and low types in the data. With this calibration strategy, the elasticity of separations to productivity shocks (at the average separation rate $\overline{s}_i$) can be written as:

$$\left.\frac{d\ln s_i}{d\ln z}\right|_{\Phi(\ln R_i,0,\sigma_\varepsilon)=\overline{s}_i} = \frac{\phi(\ln R_i,0,\sigma_\varepsilon)}{\Phi(\ln R_i,0,\sigma_\varepsilon)}\frac{d\ln R_i}{d\ln z} = \frac{\phi(\Phi^{-1}(\overline{s}_i,0,\sigma_\varepsilon),0,\sigma_\varepsilon)}{\overline{s}_i}\frac{d\ln R_i}{d\ln z},$$

where where $\Phi^{-1}(s,\mu,\sigma)$ is the inverse of the normal cdf with mean μ and standard deviation σ, and evaluated at s. The ratio of the Mills ratio of the two groups can be written as:

$$\left.\frac{M_l}{M_h}\right|_{F_\varepsilon(R_h)=\overline{s}_h,F_\varepsilon(R_l)=\overline{s}_l} = \frac{\phi(\Phi^{-1}(\overline{s}_l,0,\sigma_\varepsilon),0,\sigma_\varepsilon)}{\phi(\Phi^{-1}(\overline{s}_h,0,\sigma_\varepsilon),0,\sigma_\varepsilon)}\frac{\overline{s}_h}{\overline{s}_l}.$$

The inverse Mills ratio of the (log) normal distribution is independent of μ and scales with σ, such that, *for any μ and σ*, $\left.\frac{M_l}{M_h}\right|_{F_\varepsilon(R_h)=\overline{s}_h,F_\varepsilon(R_l)=\overline{s}_l} = 0.92$ for $\overline{s}_h = 0.0075$ and $\overline{s}_l = 0.0144$. This implies that, even if $\frac{d\ln R_i}{d\ln z}$ is the same for high- and low-ability types, the cyclicality of separations of high types is slightly higher than for low types, but far from explaining the differences in the cyclicality of the separations rates between the low and high types in the data. Table 2 in the main text of the paper shows that the ratio of the cyclicality of the separation rate for the low-wage group relative to the high-wage group is 0.43.

Moreover, the simulations of the model with the baseline calibration, which relies on differential indexation of unemployment benefits b_i, implies that $\frac{d\ln s_i}{d\ln z}$ is higher for *low* types, and thus, given the small differences in inverse Mills ratios, differences in $\frac{dR_i}{d\ln z}$ should dominate the differences in the inverse Mills ratios.

Of course, this calculation assumes a zero serial correlation in match productivities and thus it is important to determine the importance of $\widetilde{M}_i = \frac{\int \phi(\ln R_i,\rho_x \ln x_{-1},\sigma_\varepsilon)g_i(x_{-1})dx_{-1}}{\int \Phi(\ln R_i,\rho_x \ln x_{-1},\sigma_\varepsilon)g_i(x_{t-1})dx_{t-1}}$ for the cyclicality of separations in the model. To that purpose, I simulated the model (the baseline calibration) and computed $\widetilde{M}_i$ for each period for both types of workers. On average, the ratio $\frac{\widetilde{M}_l}{\widetilde{M}_h}$ was 0.97 and thus even closer to one than in the model with zero serial correlation. Moreover, this ratio tends to be very close to 1 for the various calibrations/robustness checks in the Appendix Table G.1, ranging between 0.95 and 0.99. Furthermore, in the presence of serial correlation, the differences in Mills ratios between low- and high-types is nearly unaffected by the distributional assumptions on the error terms. In simulations where I assumed that the error term followed the uniform distribution instead of the normal distribution (with zero mean and same variance), I found that $\frac{\widetilde{M}_l}{\widetilde{M}_h}$ was 0.97 for both the model with normal errors as well as the model with uniform errors. Therefore, the differences in the cyclicality of separation rates come from differences in $\frac{d\ln R_i}{d\ln z}$ rather than from differences in $\widetilde{M}_i$ across the two types of workers.

Finally, an alternative method to determine the relative importance of the two margins in equation (25) for the differences in the cyclicality of separations is to directly compute the cyclicality of R_i w.r.t. z for both groups in the model. For the baseline calibration, I find that $\frac{d\ln R_l}{d\ln z} = -0.11$ and $\frac{d\ln R_h}{d\ln z} = -0.079$, and thus the ratio of the two is equal to 1.39, which is only slightly bigger than the ratio of the cyclicality of separation rates $\frac{\frac{d\ln s_l}{d\ln z}}{\frac{d\ln s_h}{d\ln z}} = 1.33$ for the same calibration. This shows that the higher cyclicality of separations for the low-ability types in the baseline calibration is entirely driven by the higher cyclicality of R_i for the low-ability types (and confirms that the distribution of match productivities attenuates the cyclicality of separations for the low-ability types relative to the high-ability types but only to a very small degree).

G.2 The cyclicality of the reservation match productivity threshold R_i

This subsection provides analytical results on the cyclicality of the reservation match productivity threshold R_i. Since it is not possible to give a formal proof in the baseline version of the model, I consider a special case of the model where the worker has no bargaining power and match productivity x is drawn at the beginning of the employment relationship and constant thereafter.[17] In what follows, I assume that there are only aggregate productivity shocks z and no shocks to λ or γ, and, thus, the aggregate state is $Z = z$.

Proposition 5 *In the version of the model where $\alpha = 0$ and match productivity x is drawn at the beginning of the employment relationship and constant thereafter, the reservation match productivity $R_i(z)$ is proportional to $\frac{b_i}{a_i}$ in both aggregate states.*

Proof. The Nash bargaining solution implies that with $\alpha = 0$, $W_i(z,x) = U_i(z)$ and thus $w_i(z,x) = b_i$, and thus the surplus of the employment relationship can be written as[18]

$$S_i(z_j, x) = z_j x a_i - b_i + \beta \left[\pi_{jg} \max(S_i(z_g, x), 0) + \pi_{jb} \max(S_i(z_b, x), 0)\right].$$

[17]Note that in the version of the model where matches are formed at $x = \overline{x}$, it does not make much sense to assume that match productivity shocks are completely persistent because then workers and firms would never dissolve a match. Therefore, I assume here that match productivities are drawn from a distribution function $F_x(x)$.

[18]In the more general case, where $\alpha = 0$, but the natural logarithm of match productivity x follows an AR(1) process, the surplus of the employment relationship can be written as

$$S(z_j, x) = z_j x a_i - b_i + \beta \int \left[\pi_{jg} \max(S_i(z_g, q), 0) + \pi_{jb} \max(S_i(z_b, q), 0)\right] f(q|x) dq$$

where $S_i(z_j, x)$ is the total surplus of the match with worker of type i, with match-productivity x and aggregate productivity z_j, and where $\pi_{jj'}$ are the transition probabilities of the aggregate productivity state and $f(x'|x)$ is the conditional density function of match productivity state $x\prime$ in the next period conditional on x in this

Imposing the efficient separation condition $S(z_j, R_i(z_j)) = 0$, thus simplifies to

$$R_i(z_g) = \frac{b_i}{a_i}\frac{1}{z_g}$$
$$R_i(z_b) = \frac{b_i}{a_i}\frac{1}{z_g}\frac{(1-\beta\pi_{gg})z_g + \beta\pi_{bg}z_g}{(1-\beta\pi_{gg})z_b + \beta\pi_{bg}z_g}$$

which implies that $R_i(z_g) - R_i(z_b) < 0$ since $z_g > z_b$. Note that I used the fact that $S_i(z_b, R_i(z_g)) < 0$ and $S_i(z_g, R_i(z_b)) > 0$ in the derivation of this result. If one posits that $S_i(z_b, R_i(z_g)) > 0$ and $S_i(z_g, R_i(z_b)) < 0$, then ones still gets that $R_i(z_g) < R_i(z_b)$, but since $\frac{dS_i(z_g,x)}{dx} > 0$, then this implies that $S_i(z_b, R_i(z_g)) < S_i(z_b, R_i(z_b)) = 0$ and $S_i(z_g, R_i(z_b)) > S_i(z_g, R_i(z_g)) = 0$. Note also that $S_i(z_g, R_i(z_b)) = \frac{z_g R_i(z_b) a_i - b_i}{1-\beta\pi_{gg}}$. ■

Corollary 6 *In the version of the model where $\alpha = 0$ and match productivity x is drawn at the beginning of the employment relationship and constant thereafter, the change in the reservation match productivity threshold is proportional to $\frac{b_i}{a_i}$, whereas the log difference is independent of $\frac{b_i}{a_i}$.*

Proof. It follows from

$$R_i(z_g) = \frac{b_i}{a_i}\frac{1}{z_g}$$
$$R_i(z_b) = \frac{b_i}{a_i}\frac{1}{z_g}\frac{(1-\beta\pi_{gg})z_g + \beta\pi_{bg}z_g}{(1-\beta\pi_{gg})z_b + \beta\pi_{bg}z_g}$$

that

$$R_i(z_g) - R_i(z_b) = \frac{b_i}{a_i}\frac{1}{z_g}\left[1 - \frac{(1-\beta\pi_{gg})z_g + \beta\pi_{bg}z_g}{(1-\beta\pi_{gg})z_b + \beta\pi_{bg}z_g}\right],$$

and

$$\ln(R_i(z_g)) - \ln(R_i(z_b)) = -\ln\frac{(1-\beta\pi_{gg})z_g + \beta\pi_{bg}z_g}{(1-\beta\pi_{gg})z_b + \beta\pi_{bg}z_g}.$$

■

In other words, in this very special case, the cyclicality of the reservation threshold R_i is independent of type.

period. The efficient-separation condition implies

$$R_i(z_j) = \frac{b_i}{z_j a_i} - \beta\int\left[\frac{\pi_{jg}}{z_j}\frac{\max(S_i(z_g,q),0)}{a_i} + \frac{\pi_{jb}}{z_j}\frac{\max(S_i(z_b,q),0)}{a_i}\right]f(q|R_i(z_j))dq.$$

It is not possible to derive a closed form solution for $R_i(z_j)$ in this more general case.

G.3 Robustness checks for the baseline calibration

The results in the paper and Section G.1 here in the Appendix show that, in the baseline calibration of the model, low-ability type workers have more cyclical separations and that this is driven by more cyclical reservation productivities for low-ability workers. Given that these results cannot be proven formally for the general model and given that it does not hold in the very special case in the previous subsection, it is important to show the robustness of these results to reasonable parameter choices. The propositions in the section G.2 applied only to a very special case of the model, which made two main simplifying assumptions:

1. Zero bargaining share of the worker: When $\alpha = 0$, the value of unemployment is $\frac{b}{1-\beta}$ and thus does not depend on the state of the business cycle. When $\alpha > 0$, then the value of the outside option of the unemployed worker varies with the business cycle both because the value of the match for the worker W and the job finding rate improve in good times and worsen in bad times. If the outside option of the unemployed worker becomes more cyclical, this tends to make separations less cyclical. It is therefore an important robustness check to see whether the baseline results are sensitive to the calibration of the worker's bargaining share α, and, in particular, whether the results go through for low values of α.

2. With constant match-specific productivity, separations only occur among matches that were started in good times. When $\sigma_\varepsilon > 0$ and $\rho_x < 1$, then the option value of waiting for an improvement in match-specific productivity becomes an important determinant for the reservation match productivity, and thus it is important to see whether the results in the baseline calibration are sensitive to the choices of parameter values for σ_ε and ρ_x.

Table G.1 reproduces the simulation results from the baseline calibration where $\alpha = 0.5$, $\rho_x = 0.98$ and $\sigma_\varepsilon = 0.0275$ (Panel A.1), as well as simulation results for nine robustness checks:

- Panels A.2 and A.3 show results for $\sigma_\varepsilon = 0.015$ and $\sigma_\varepsilon = 0.06$. For both calibrations, separations are more cyclical for low-ability workers compared to high-ability workers. The differences in the cyclicalities between the two types of workers are stronger for the calibration with $\sigma_\varepsilon = 0.06$, as this calibration requires a stronger degree of non-proportionality in flow-values of unemployment to match the average separation rates. The results also highlight the general tension in search models between amplifying aggregate productivity shocks and generating reasonable amounts of wage dispersion (see Hornstein, Krusell and Violante (2011) for a detailed analysis of this issue): While the low σ_ε (= high b) calibration generates more cyclical volatility, it generates a tiny amount dispersion in wage changes. The opposite is the case for the high σ_ε (= low b) calibration.

- Panels A.4 and A.5 show that the results are sensitive to the choice for ρ_x, as for $\rho_x = 0.9$ separations for low- and high-ability workers are about equally cyclical. Panel B.1 shows an even more extreme calibration where $\rho_x = 0.9$ and $\sigma_\varepsilon = 0.015$. This calibration produces slightly more cyclical separations for high-wage workers (the fact that the pre-displacement wage remains slightly procyclical is due to differences in the cyclicality of job finding rates). Note, however, that all these calibrations produce a counterfactually low auto-correlation of log wages: the AR(1) coefficient is 0.89 in this calibration of the model, compared to 0.98-0.99 in the data. Note that these are monthly AR(1) coefficients and thus small differences give rise to large differences in yearly AR(1) coefficients. In other words, calibrations with $\rho_x = 0.9$ and even the one with $\rho_x = 0.95$ are clearly at odds with the persistence of wages in the data.

- Panels B.2 and B.3 show that separations of low-ability workers remain more cyclical for low values of the worker's bargaining power α. Note that these calibrations generate a tiny amount of dispersion in wage changes, as wages are closely related to b (in the extreme case, where $\alpha = 0$, then wages are set equal to b at all times).

- Panels B.4 and B.5 show that the pre-displacement wage becomes slightly less pro-cyclical for a calibration where the elasticity of the matching function is set to 0.72 (as in Shimer, 2005) and for a calibration where the average duration of recession is set to 11.1 months (=the average length of a U.S. recession in the postwar era). However, this is driven by smaller differences in the cyclicality of job finding rates. In fact, the differences in the cyclicality of separation rates are slightly larger for both of these calibrations compared to the baseline calibration.

To sum up, the result that separations are more cyclical for low-ability type workers appears to be a robust feature of calibrations that choose the parameter b_i so as to match group-specific average separation rates. The results are most sensitive to the parameter ρ_x, but one would have to choose a very low value of ρ_x to overturn the main result of the baseline calibration, which would produce a counterfactually low autocorrelation of wages in the model.

G.4 Robustness checks for the model with firm death

Panels B.2 to B.6 in Table G.2 show robustness checks for the model with firm death shocks. The baseline version here (reproduced in Panel B.1) relies on a calibration of the shock to the cyclical volatility of firm death in the BDS data (see Table G.6), which has a standard deviation of 0.04% in the data. As already discussed in the paper, the success of the model depends crucially on the relative variance of aggregate productivity shocks z and firm death shocks λ and the amplification of productivity shocks in the model: The model does worse for a calibration with a high flow value of unemployment (Panel B.3) compared to a model with a low flow value of unemployment (Panel B.2), as the low flow value tends to lead to less amplification of productivity shocks on both the separation and the job finding margin. A model with no productivity shocks (Panel B.4) produces a highly pro-cyclical pre-displacement wage, but this is clearly unrealistic as it does not generate any volatility in job finding. A model where the volatility of firm death shocks is calibrated to mass layoff data, tends to perform better, but the interpretation of mass layoffs is different from firm death and it is less clear whether they are completely indiscriminate. In fact, mass layoffs tend be often associated with high quit rates as shown by Davis, Faberman and Haltiwanger (2012).

G.5 Extension to model with cyclical productivity dispersion

Panels A.1 to A.5 in Table G.4 show robustness checks for the model with counter-cyclical productivity dispersion calibrated the same way as in the model without ex-ante heterogeneity. As for the model with firm death shocks, the success of the model depends on the relative variance of aggregate productivity shocks z and dispersion shocks as well as the amplification of productivity shocks in the model: The model does worse for a calibration with a high flow value of unemployment (Panel A.3) compared to a model with a low flow value of unemployment (Panel A.2), as the low flow value tends to lead to less amplification of productivity shocks on both the separation and the job finding margin. Overall, the results for this model are mixed and only calibrations with very low flow values of unemployment appear to generate a counter-cyclicality of the pre-displacement wage of similar magnitude as in the data. In fact, the results in Panel A.2 rely on a calibration where the flow-value of unemployment for the high-wage worker is lower than for the low-wage worker, not only relative to productivity a_i, but also in absolute terms, which clearly goes against the idea that consumption and leisure tend to be complements. Kehrig also shows that the cross-sectional productivity dispersion spiked up sharply in the Great Recession, but as Figure 3 in the paper shows, the compositional shifts among the unemployed were not unusually strong over that period.

G.6 Robustness checks for model with heterogeneity in σ_ε

Panels A.2 to A.6 in Table G.2 show robustness checks for the alternative calibration strategy that chooses the parameter $\sigma_{\varepsilon,i}$ so as to match group-specific average separation rates. The baseline for this alternative calibration from Table 4 in the paper is shown in Panel A.1, which sets the flow-value of unemployment b to 0.71 as in Hall and Milgrom (2008). Panels A.2, A.3 and A.4 show that the results are similar for different assumptions about the level of the flow-value of unemployment b, the bargaining share α and the auto-correlation coefficient ρ_x.

Note that all these calibrations predict that the standard deviation of log wage changes is about twice as high for low-ability workers in contrast to the empirical results shown in Table G.4, which reveal that the dispersion of wage changes tends to be similar across groups in the CPS data and NLYS79 data. Most importantly, the standard deviation of yearly log wage changes appears to be nearly same below and above the median wage for the sample of job stayers in row 4 of Table G.5. The sample of job stayers is the relevant sample to assess the dispersion of *match-specific* shocks, as otherwise estimates would be confounded by wage changes associated with employer changes.[19] As mentioned in the paper, however, one issue with this exercise is that measurement error in surveyed wages may be too large to draw meaningful inferences from this comparison. 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.

G.6.1 A back-of-the-envelope calculation on the extent of measurement error in log wage changes across years. To provide some further clarity on the issue of measurement error in surveyed wages, I provide here a simple back-of-the-envelope calculation on the extent of measurement error in yearly log wage changes:

- Comparing survey data to administrative data on earnings, Bound and Krueger (1991) find that about 13 percent of the total variance of earnings are explained by measurement error.

- If we assume that the log wage of worker i at time t, $\log W_{it}$, can be decomposed into a fixed worker effect, w_i^a, an aggregate time effect, w_t^d, a match-specific component, w_{it}^x, and a measurement error component, w_{it}^e, in the following form

$$\log W_{it} = w_i^a + w_t^d + w_{it}^x + w_{it}^e,$$

and denote $\log \tilde{W}_{it}$ as the wage adjusted for aggregate time effects (i.e., $\log \tilde{W}_{it} = \log W_{it} - w_t^d$), then the variance of log wage innovations (adjusted for aggregate time effects) is

$$Var(d \log \tilde{W}_{it}) = Var(w_{it}^x - w_{it-1}^x) + Var(w_{it}^e - w_{it-1}^e).$$

- If we assume that w_{it}^e is identically distributed across time but is potentially serially correlated across survey waves, with a correlation coefficient of ρ_e, then

$$Var(d \log \tilde{W}_{it}) = Var(w_{it}^x - w_{it-1}^x) + 2Var(w_{it}^e)(1 - \rho_e).$$

[19] As is to be expected, the dispersion of wage changes is somewhat larger for samples that include employer changes (see rows 1-3 in Table G.5).

- While it is unclear to what extent measurement error is correlated across survey waves, I provide here a possible upper bound on the issue of measurement error, by assuming that $\rho_e = 0$.[20] If $\rho_e = 0$ and using the 13 percent figure from Bound and Krueger (1991), we get

$$2Var(w_{it}^e)(1 - \rho_e) = 2 * 0.13Var(\log W_{it})$$

and thus the share of the variance in log wage innovations explained by measurement error, denoted S, is

$$S = \frac{2 * 0.13Var(\log W_{it})}{Var(d \log \tilde{W}_{it})}$$

- In the matched CPS ORG data, $Var(\log W_{it}) = 0.33$ and $Var(d \log \tilde{W}_{it}) = 0.11$, and thus

$$S = \frac{2 * 0.13 * 0.33}{0.11} = 0.78,$$

i.e., up to 78 percent of the observed variance in log wage innovations may be accounted for by measurement error.

G.7 Other forms of ex-ante worker heterogeneity

All explanations discussed so far focused on worker heterogeneity in terms of market productivity a as the main source of wage dispersion across workers. However, one may argue that other forms of heterogeneity would create wage dispersion across workers and at the same time be consistent with the empirical patterns documented in this paper.

The following briefly discusses simulation results for three other forms of worker heterogeneity, where a_i is set to 1 for both groups of workers (the results are shown in Table G.3):

1. *Heterogeneity in b*: 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, the fundamental difficulty with this approach is that it results in a higher *average* separation rate for the high-wage workers, which is in contradiction with the data. Furthermore, the magnitude of the compositional shifts in terms of the pre-displacement wage is more than 10 times smaller than in the data. The main reason for the small magnitude is that the wage differences between low- and high-b workers are relatively small, despite substantial differences in the calibrated b_i. The reason for this is that the wage bargaining set is substantially smaller than the difference between

[20] Of course, it is theoretically conceivable that the measurement error is negatively serially correlated, in which case, $\rho_e = 0$ does not imply an upper bound for $2Var(w_{it}^e)(1 - \rho_e)$.

the marginal product and the flow-value of unemployment, due to the option value of unemployment. To explore whether the results are sensitive to calibration choices that affect the wage differential between high- and low-b workers, I simulate a version of the model where I set α to 0.75, which does little to affect the magnitude of the compositional shifts.

2. *Heterogeneity in* α: One may argue that the empirical results are driven by workers who are better at extracting surplus from a working relationship, captured by a higher bargaining share α. However, the simulation results in Panels A.3 and A.4 in Table G.3 show that cyclicality of separations for these workers tends to be lower, not higher, compared to workers with a lower bargaining share α. The reason is that a higher α tends to make the outside option of the worker more pro-cyclical and thus separations less counter-cyclical. Given these results, it is surprising that the pre-displacement wage appears to be slightly counter-cyclical. The reason for this is that - while the average log wage is higher for the group with the high α - the average pre-displacement wage is actually lower for the high-α type workers, because the group with the high bargaining power α faces more wage dispersion. In the presence of serially correlated match productivity, workers at the bottom of the wage distribution are much more likely to separate, and thus high-α workers have a lower pre-displacement wage despite higher average wages compared to low-α workers.

TABLE G.1 ROBUSTNESS CHECKS FOR THE BASELINE MODEL WITH EX-ANTE HETEROGENEITY

Statistic:	***A.1*** *Baseline*		***A.2*** $\sigma_\varepsilon = 0.015$		***A.3*** $\sigma_\varepsilon = 0.06$		***A.4*** $\rho_x = 0.95$		***A.5*** $\rho_x = 0.90$	
Cyclicality of aggregate										
… log pre-displacement wage	-2.12		-1.72		-3.98		-1.21		-0.14	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.78	0.61	0.86	0.72	0.68	0.25	0.88	0.76	0.85	0.87
… log job finding rates	-0.55	-0.26	-0.49	-0.23	-0.75	-0.36	-0.42	-0.27	-0.35	-0.26
… log unemployment rates	1.13	0.75	1.10	0.81	1.25	0.53	1.07	0.86	1.01	0.98
… log reservation productivities	0.040	0.029	0.022	0.017	0.078	0.029	0.034	0.027	0.027	0.024
Aggregate time-series statistics:										
Std(log separation rate)	0.053		0.110		0.014		0.095		0.176	
Std(log job finding rate)	0.022		0.038		0.010		0.030		0.052	
Std(log unemployment rate)	0.047		0.087		0.015		0.075		0.151	
Cross-sectional statistics:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
Std(log wage changes)	0.04	0.04	0.02	0.02	0.10	0.10	0.04	0.04	0.04	0.04
AR(1) coefficient of log wages	0.98	0.97	0.98	0.97	0.98	0.97	0.94	0.94	0.89	0.89
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.81	0.52	0.89	0.73	0.59	-0.06	0.84	0.72	0.90	0.85
$\sigma_{\varepsilon,i}$	0.028	0.028	0.015	0.015	0.060	0.060	0.028	0.028	0.028	0.028
c_i	0.14	0.71	0.07	0.40	0.31	1.60	0.10	0.40	0.06	0.21

Statistic:	***B.1*** $\rho_x = 0.90$, $\sigma_\varepsilon = 0.015$		***B.2*** $\alpha=0.1$		***B.3*** $\alpha=0.1$, $\sigma_\varepsilon = 0.015$		***B.4*** $\eta = 0.72$		***B.5*** $\pi_{bg}=1/11.1$, $\pi_{gb}=1/59.5$	
Cyclicality of aggregate										
… log pre-displacement wage	-0.04		-1.35		-1.32		-1.61		-1.55	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.84	0.89	0.89	0.79	0.86	0.78	1.19	0.92	0.89	0.72
… log job finding rates	-0.31	-0.23	-0.44	-0.22	-0.42	-0.21	-0.22	-0.11	-0.46	-0.22
… log unemployment rates	1.00	0.99	1.08	0.85	1.08	0.86	1.10	0.82	1.10	0.82
… log reservation productivities	0.014	0.014	0.039	0.034	0.022	0.019	0.048	0.036	0.040	0.030
Aggregate time-series statistics:										
Std(log separation rate)	0.343		0.162		0.308		0.076		0.049	
Std(log job finding rate)	0.091		0.050		0.091		0.011		0.015	
Std(log unemployment rate)	0.293		0.123		0.235		0.050		0.037	
Cross-sectional statistics:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
Std(log wage changes)	0.02	0.02	0.01	0.01	0.00	0.00	0.04	0.04	0.04	0.04
AR(1) coefficient of log wages	0.89	0.89	0.98	0.97	0.98	0.97	0.98	0.97	0.98	0.97
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.94	0.92	1.00	0.92	1.00	0.95	0.81	0.51	0.82	0.52
$\sigma_{\varepsilon,i}$	0.015	0.015	0.028	0.028	0.015	0.015	0.028	0.028	0.028	0.028
c_i	0.04	0.12	0.25	1.31	0.14	0.72	0.14	0.73	0.14	0.72

Notes: See Table 4 for details.

TABLE G.2 ROBUSTNESS CHECKS FOR THE ALTERNATIVE CALIBRATION AND FOR THE MODEL WITH FIRM DEATH SHOCKS

Statistic:	***A.1*** *Alternative calibration (b/a = 0.71)*		***A.2*** *Alternative calibration (b/a=0.4)*		***A.3*** *Alternative calibration (b/a=0.9)*		***A.4*** *Alternative calibration (α = 0.1, b/a=0.9)*		***A.5*** *Alternative calibration (ρ_x = 0.9)*		***A.6*** *Alternative calibration (π_{bg}=1/11.1, π_{gb}=1/59.5)*	
Cyclicality of aggregate												
… log pre-displacement wage	4.24		4.08		4.75		3.00		2.04		4.42	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.56	1.25	0.44	1.00	0.60	1.38	0.69	1.20	0.68	1.02	0.59	1.28
… log job finding rates	-0.39	-0.42	-0.51	-0.54	-0.31	-0.38	-0.36	-0.35	-0.38	-0.38	-0.34	-0.37
… log unemployment rates	0.77	1.44	0.80	1.38	0.73	1.51	0.84	1.31	0.89	1.21	0.75	1.46
… log reservation productivities	0.04	0.03	0.06	0.06	0.01	0.01	0.06	0.05	0.06	0.06	0.04	0.04
Aggregate time-series statistics:												
Std(log separation rate)	0.060		0.019		0.165		0.107		0.063		0.048	
Std(log job finding rate)	0.021		0.010		0.048		0.032		0.022		0.014	
Std(log unemployment rate)	0.047		0.018		0.126		0.081		0.054		0.037	
Cross-sectional statistics:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
Std(log wage changes)	0.06	0.03	0.12	0.05	0.02	0.01	0.02	0.01	0.10	0.07	0.06	0.03
AR(1) coefficient of log wages	0.98	0.97	0.97	0.97	0.98	0.97	0.97	0.97	0.89	0.89	0.98	0.97
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.71	0.71	0.40	0.40	0.90	0.90	0.90	0.90	0.71	0.71	0.71	0.71
$\sigma_{\varepsilon,i}$	0.037	0.016	0.071	0.033	0.016	0.006	0.052	0.027	0.074	0.054	0.038	0.017
c_i	0.18	0.43	0.27	0.78	0.07	0.15	0.40	1.16	0.16	0.39	0.17	0.41

Statistic:	***B.1*** *Baseline with λ shocks*		***B.2*** *λ shocks, σ_ε = 0.04*		***B.3*** *λ shocks, σ_ε = 0.015*		***B.4*** *λ shocks, but no z shocks*		***B.5*** *λ shocks (calibrated to BED data)*		***B.6*** *λ shocks (calibrated to mass layoffs)*	
Cyclicality of aggregate												
… log pre-displacement wage	-0.20		0.87		-1.68		5.36		-1.17		1.51	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.78	0.90	0.77	1.00	0.88	0.79	0.78	1.56	0.84	0.81	0.79	1.10
… log job finding rates	-0.36	-0.16	-0.33	-0.15	-0.41	-0.18	-0.04	-0.04	-0.41	-0.17	-0.29	-0.14
… log unemployment rates	1.04	0.93	0.99	1.01	1.10	0.81	0.74	1.49	1.09	0.84	0.95	1.09
… log reservation productivities	0.03	0.01	0.03	-0.01	0.02	0.01	-0.01	-0.02	0.04	0.01	0.02	0.00
Aggregate time-series statistics:												
Std(log separation rate)	0.050		0.038		0.087		0.025		0.045		0.085	
Std(log job finding rate)	0.015		0.010		0.026		0.001		0.014		0.019	
Std(log unemployment rate)	0.051		0.037		0.074		0.022		0.041		0.076	
Cross-sectional statistics:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
Std(log wage changes)	0.04	0.05	0.07	0.07	0.02	0.02	0.04	0.05	0.04	0.05	0.04	0.05
AR(1) coefficient of log wages	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.66	0.11	0.50	-0.28	0.81	0.51	0.66	0.11	0.65	0.08	0.75	0.37
$\sigma_{\varepsilon,i}$	0.028	0.028	0.040	0.040	0.015	0.015	0.028	0.028	0.028	0.028	0.028	0.028
c_i	0.21	1.22	0.30	1.77	0.11	0.68	0.21	1.23	0.21	1.27	0.16	0.91

Notes: See Table 4 for details.

TABLE G.3 OTHER FORMS OF EX-ANTE HETEROGENEITY

Statistic:	***A.1*** *Calibrate b_i to match $E(s_i)$*		***A.2*** *Calibrate b_i to match $E(s_i)$*		***A.3*** *Calibrate α_i to match $E(s_i)$*		***A.4*** *Calibrate α_i to match $E(s_i)$*	
Cyclicality of aggregate								
… log pre-displacement wage	0.19		0.19		0.04		0.01	
Cyclicality of group-specific	b_{low}	b_{high}	b_{low}	b_{high}	α_{low}	α_{high}	α_{low}	α_{high}
… log separation rates	0.55	0.82	0.55	0.79	1.13	0.62	0.87	0.44
… log job finding rates	-0.26	-0.55	-0.29	-0.60	-0.39	-0.44	-0.51	-0.58
… log unemployment rates	0.71	1.15	0.71	1.16	1.28	0.86	1.25	0.86
… log reservation productivities	0.03	0.04	0.02	0.04	0.05	0.03	0.09	0.05
Average of group-specific	b_{low}	b_{high}	b_{low}	b_{high}	α_{low}	α_{high}	α_{low}	α_{high}
… separation rates	0.008	0.014	0.008	0.014	0.007	0.014	0.008	0.014
… job finding rates	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
… unemployment rates	0.023	0.044	0.024	0.045	0.024	0.045	0.024	0.045
… log wages	0.04	0.06	0.05	0.07	0.03	0.07	0.09	0.15
… log pre-displacement wages	-0.05	-0.01	-0.08	-0.04	-0.02	-0.04	-0.02	-0.06
Aggregate time-series statistics:								
Std(log separation rate)	0.054		0.035		0.052		0.015	
Std(log job finding rate)	0.022		0.015		0.019		0.009	
Std(log unemployment rate)	0.046		0.029		0.041		0.015	
Cross-sectional statistics:	b_{low}	b_{high}	b_{low}	b_{high}	α_{low}	α_{high}	α_{low}	α_{high}
Std(log wage changes)	0.04	0.04	0.07	0.06	0.03	0.06	0.06	0.13
AR(1) coefficient of log wages	0.97	0.98	0.97	0.98	0.97	0.98	0.97	0.98
Group-specific parameters: *(internally calibrated parameters in **bold**)*	b_{low}	b_{high}	b_{low}	b_{high}	α_{low}	α_{high}	α_{low}	α_{high}
a_i	1	1	1	1	1	1	1	1
b_i	**0.52**	**0.81**	**0.27**	**0.69**	0.71	0.71	0.40	0.40
$\sigma_{\varepsilon,i}$	0.028	0.028	0.028	0.028	0.028	0.028	0.060	0.060
α_i	0.50	0.50	0.75	0.75	**0.31**	**0.72**	**0.30**	**0.68**
c_i	**0.51**	**0.24**	**0.25**	**0.12**	**0.70**	**0.13**	**1.54**	**0.34**

Notes: See Table 4 for details.

TABLE G.4 ROBUSTNESS CHECKS FOR THE MODEL WITH EX-ANTE HETEROGENEITY AND DISPERSION SHOCKS

Statistic:	***A.1*** *Dispersion shocks (baseline)*		***A.2*** *Dispersion shocks (σ_ε = 0.06)*		***A.3*** *Dispersion shocks (σ_ε = 0.015)*		***A.4*** *Dispersion shocks (σ_ε = 0.06, ρ_x = 0.9)*		***A.5*** *Smaller dispersion shocks (std = 2.5%)*	
Cyclicality of aggregate										
… log pre-displacement wage	0.16		1.89		-1.11		0.69		-1.16	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.89	1.06	1.09	1.54	0.80	0.76	0.93	1.18	0.77	0.74
… log job finding rates	-0.24	-0.12	-0.15	-0.11	-0.35	-0.19	-0.20	-0.15	-0.45	-0.25
… log unemployment rates	1.01	0.97	0.94	1.15	1.07	0.85	1.00	1.01	1.08	0.84
… log reservation productivities	0.00	-0.01	-0.02	-0.02	0.01	0.00	-0.01	-0.02	0.01	0.00
Aggregate time-series statistics:										
Std(log separation rate)	0.081		0.083		0.101		0.081		0.057	
Std(log job finding rate)	0.030		0.025		0.043		0.029		0.033	
Std(log unemployment rate)	0.072		0.049		0.114		0.066		0.061	
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.78	0.47	0.59	0.06	0.89	0.72	0.69	0.19	0.82	0.53
$\sigma_{\varepsilon,i}$	0.028	0.028	0.060	0.060	0.015	0.015	0.028	0.028	0.028	0.028
c_i	0.27	0.55	0.55	1.02	0.13	0.29	0.12	0.28	0.23	0.49

Notes: See Table 4 for details.

TABLE G.5 THE STANDARD DEVIATION OF LOG WAGE CHANGES, BY WAGE AND EDUCATION GROUP

					By wage group		By residual wage group		By education group	
	Data Source:	Type of jobs:	Excluding employer changes:	N	Below median	Above median	Below median	Above median	HS degree or less	Some college or more
(1)	CPS ORG	Main job at time of interview	No	3,812,912	0.33	0.35	0.34	0.34	0.31	0.38
(2)	NLSY79	All jobs in survey year	No	97,487	0.46	0.42	0.41	0.41	0.46	0.43
(3)	NLSY79	Main job at time of interview	No	90,393	0.33	0.33	0.32	0.33	0.34	0.38
(4)	NLSY79	Main job at time of interview	Yes	69,435	0.27	0.28	0.27	0.28	0.28	0.32

Notes: The estimates from the matched CPS ORG sample reported in row (1) show the standard deviation of the changes in the natural logarithm of the hourly wage between interviews 4 and 8 (which are exactly one year apart). The sample is restricted to individuals who are matched across these two interviews and who have wage observations in both years. All other sample restrictions are the same as for the estimates presented in Section 3 of the paper. The estimates from the NLSY79 reported in rows (2)-(4) show the standard deviation of the changes in the natural logarithm of the hourly wage between two consecutive interviews (on average one year for the period 1994 and earlier, and on average two years for the period after 1994). All other sample restrictions are the same as for the estimates presented in Section 2 of the paper. The sample was split in columns (1) and (2) below and above the median wage based on the wage in the previous interview. The sample was split in columns (3) and (4) below and above the median residual wage (for the NLSY79 this refers to the residual of the second stage regression, which controls for individual fixed effects). The sample was split in columns (5) and (6) based on educational attainment in the previous interview. Source: The author's estimates with the matched CPS ORG sample for the years 1979 to 2012, and with data from the NLSY79 for the years 1979 to 2012.

TABLE G.6 THE VOLATILITY OF THE JOB DESTRUCTION RATE AT DYING/CLOSING ESTABLISHMENTS

Data Source:	*Business Dynamics Statistics (Census) 1977-2012*	*Business Employment Dynamics (BLS) 1992-2014*	*Mass Layoff Rate (BLS) 1995-2012*
Variable:	*Job Destruction Rate at Dying Establishments*	*Job Destruction Rate at Closing Establishments*	*Mass Layoff Rate*
Frequency:	*Yearly*	*Quarterly*	*Monthly*
Average	5.30%	1.36%	0.19%
Average, expressed in monthly frequency	0.45%	0.46%	0.19%
Standard deviation of hp-filtered series	0.49%	0.10%	0.08%
Standard deviation of hp-filtered series, expressed in monthly frequency	0.04%	0.03%	0.08%

Sources: The author's estimates with yearly data from the Business Dynamics Statistics (Census) for the years 1977-2012, with quarterly data from the Business Employment Dynamics (BLS) for the years 1992-2014 on the job destruction rate at closing establishments (Series Id: BDS0000000000000000110006RQ5) and with monthly data from Mass Layoff Statistics (BLS) for the years 1995-2012 of the number of new UI claimants laid off in a mass layoff (Series Id: MLSMS00NN0119005).
Notes: Closing establishment includes establishments that shut down temporarily for a few quarters. Mass layoffs are defined as events where employers are filed 50 UI claims or more against over a 5-week period. To compute the monthly mass layoff rate, the number of new claimants laid off in a mass layoff is divided by total employment in firms with more than 50 employees from the Business Dynamics Statistics in that year. The HP-smoothing parameter 100 is used for yearly data, the parameter 100,000 for quarterly data and the parameter 900,000 for monthly data.

Appendix H. A search-matching model with cyclical cash-flow constraints

This appendix sets up a search-matching model with cyclical cash-flow constraints. The notation closely follows the notation of the benchmark model in the paper.

H.1 Value functions, wage setting and equilibrium

The value function of an unemployed worker of type i is:

$$U_i(Z) = b_i + \beta E\left[(1 - f(\theta_i))U_i(Z') + f(\theta_i)W_i(Z', \bar{x})\right| Z], \tag{26}$$

where $Z = [z, \lambda, \gamma]$ is the aggregate state, z is aggregate productivity, λ is an indiscriminate separation shock and γ is the cash-flow constraint.[21] The value of being unemployed depends on the unemployment benefit, b_i, which potentially depends on worker type, and the discounted value of remaining unemployed in the next period or having a job with the value $W_i(Z', \bar{x})$.

The value function of an employed worker of type i is:

$$W_i(Z,x) = w_i(Z,x) + \beta E\left[\begin{array}{c} (1-\lambda)(1-\lambda_i^f(Z',x'))\max\{W_i(Z',x'), U_i(Z')\} \\ +(\lambda + (1-\lambda)\lambda_i^f(Z',x'))U_i(Z') \end{array}\middle| Z, x\right], \tag{27}$$

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 $U_i(Z')$ in the next period. $\lambda_i^f(Z,x)$ is an indicator function for whether the firm's share of the total surplus is negative in state (Z,x) and thus whether the firm will fire the worker. More precisely,

$$\lambda_i^f(Z,x) = \begin{cases} 1 & \text{if } J_i(Z,x) - V_i(Z) < 0 \\ 0 & \text{if } J_i(Z,x) - V_i(Z) \geq 0 \end{cases}.$$

The value of a vacancy of a firm searching for a worker of type i is:

$$V_i(Z) = -c_i + \beta E\left[(1 - q(\theta_i))V_i(Z') + q(\theta_i)J_i(Z', \bar{x})\right| Z], \tag{28}$$

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

The value of a vacancy filled with a worker of type i is:

[21] Equations (26) and (28) 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 and for both types of workers for all calibrations considered in this Appendix.

$$J_i(Z,x) = zxa_i - w_i(Z,x) + \beta E \left[\begin{array}{c} (1-\lambda)(1-\lambda_i^w(Z',x')) \max\{J_i(Z',x'), V_i(Z')\} \\ +(\lambda + (1-\lambda)\lambda_i^w(Z',x'))V_i(Z') \end{array} \middle| z, x \right], \quad (29)$$

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 $V_i(Z')$ in the next period. $\lambda_i^w(Z,x)$ is an indicator function for whether the worker's share of the total surplus is negative in state (Z,x) and thus whether the worker will quit. More precisely,

$$\lambda_i^w(Z,x) = \begin{cases} 1 & \text{if } W_i(Z,x) - U_i(Z) < 0 \\ 0 & \text{if } W_i(Z,x) - U_i(Z) \geq 0 \end{cases} .$$

Separations occur whenever the share of the surplus appropriated by either the worker or the firm is negative, and thus the reservation match-specific productivities, i.e. the level of match-specific productivity x below which the worker quits or the firm fires the worker, satisfy:

$$W_i(Z, R_i^w(Z)) - U_i(Z) = 0, \quad (30)$$

$$J_i(Z, R_i^f(Z)) - V_i(Z) = 0. \quad (31)$$

As explained in the paper, worker-firm matches face a constraint to produce cash flows above some number $-\gamma$:

$$CF_i(Z,x) = zxa_i - w_i(Z,x) \geq -\gamma, \quad (32)$$

where γ is stochastic. Naturally, workers may be willing to deviate from the Nash-bargained wage and take a wage cut in order to continue the relationship. For this reason, wages are assumed to satisfy the Nash-bargaining solution $w_i^{NB}(Z,x)$ as long as the cash-flow constraint (32) is met but otherwise adjust to meet the constraint[22]:

$$w_i(Z,x) = \begin{cases} w_i^{NB}(Z,x) & \text{if } zxa_i - w_i^{NB}(Z,x) \geq -\gamma \\ zxa_i + \gamma & \text{if } zxa_i - w_i^{NB}(Z,x) < -\gamma. \end{cases} \quad (33)$$

The Nash-bargained wage satisfies the standard Nash-bargaining solution:

$$w_i^{NB}(Z,x) = \arg\max_{w_i} \left[(W_i(Z,x) - U_i(Z))^{\alpha} (J_i(Z,x) - V_i(Z))^{1-\alpha} \right] \quad (34)$$

[22] 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.

where α is the bargaining share of the worker.

Definition 7 *A directed-search equilibrium with cash-flow constraints is defined as the workers' reservation match productivities $R_i^w(Z)$, the firms' reservation match productivities $R_i^f(Z)$, the wage schedules $w_i(Z,x)$, the Nash-wage schedules $w_i^{NB}(Z,x)$, 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 worker-separation condition (30), the firm-separation condition (31), the wage schedule (33), the Nash-bargaining solution (34), the zero-profit condition $V_i(Z) = 0$, and the value functions (26)-(29).*

H.2 Propositions and proofs

The important insight for the results in the paper 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 above, the firm's cash flows at the reservation productivity level $R_i(Z)$ can be written as:

$$CF_i(Z, R_i(Z)) = -\beta E\left[\ \max\left\{(1-\alpha)S_i(Z',x'),0\right\}\ \middle|\ Z, R_i(Z)\right]. \tag{35}$$

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.[23] 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 γ. In other words, marginal high-ability workers are the first ones to go when wages are cut due to a binding cash-flow constraint.[24]

If workers are willing to take wage cuts to continue the relationship, one may wonder whether cash-flow constraints will ever result in separations. It should be kept in mind, however, that workers are willing to take wage cuts only as long as their share of the surplus remains positive.

[23] As shown further below, both channels are important as there are compositional shifts in the pool of unemployed even if the cash flow constraint is proportional to ability.

[24] The results in Table 4 show that, as for the baseline model, the differences in the cyclicality of separation rates are mainly driven by differences in the cyclicality of (worker) reservation productivities.

At the efficient-separation level of match productivity $R_i(Z)$, for example, workers are not willing to take any wage cut because their surplus from the match is zero. Therefore, a binding cash-flow constraint will always lead to the separation for the matches whose productivity is at, or below, the efficient-separation level of match productivity $R_i(Z)$. For worker-firm matches with $x > R_i(Z)$, there is some room for wage adjustment. However, the actual wage cut that the worker may be willing to take is small because the surplus for those x close to $R_i(Z)$ is small.

This section lays out propositions and proofs that show that cash-flow constraints will result in separations if sufficiently tight, and that cash flow constraints are more binding for high-ability workers. The latter relies on the fact that cash flows are more negative at the efficient reservation match productivity level for high-ability workers than for low-ability workers for two reasons: First, because flow values of unemployment b_i are not fully proportional to worker productivity a_i, the reservation match productivity $R_i(Z)$ is lower and thus cash flows are more negative at $R_i(Z)$. Second, match surpluses at a given level of x and z are increasing in ability a_i, which implies that cash flows are more negative for high ability workers even if $R_i(Z)$ is the same for both types. For both of these reasons, separations of high-ability workers are more sensitive to a tightening of credit.[25]

Note that, for the purpose of tractability, I assume here that there are no indiscriminate separation shocks, i.e. $\lambda = 0$ at all times.

Proposition 8 *In the model without binding cash-flow constraints, at the efficient reservation match productivity $R_i(Z)$, the firm's cash flows are negative if the firm's bargaining share is larger than 0.*[26]

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

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

[25] To quantitatively separate the importance of the two channels, Table H provides 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.

[26] For the purpose of tractability, I assume that there are no indiscriminate separation shocks, i.e. $\lambda = 0$ at all times.

and thus

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

where $S_i(Z, x)$ is the surplus of the match, which is split according to Nash-bargaining rule in the absence of binding cash-flow constraints. This implies that cash flows have to be negative at the efficient reservation match productivity threshold if the firm expects a surplus from the match in the future, i.e. if the firm's surplus share is positive $(1 - \alpha > 0)$. This holds for any process of match productivity with some positive probability of a higher match productivity in future periods. ■

Proposition 9 *In the model without binding cash-flow constraints, at the efficient reservation match productivity $R_i(Z)$, the worker is not willing to accept a wage below the Nash-bargained wage and thus will quit if the wage is cut.*

Proof. At the efficient reservation match productivity, $S_i(Z, R_i(Z)) = 0$. Nash-bargaining implies that $W_i(Z, R_i(Z)) - U_i(Z) = \alpha S_i(Z, R_i(Z))$ and thus $W_i(Z, R_i(Z)) - U_i(Z) = 0$. Since $W_i(Z, R_i(Z))$ is increasing in the current wage (all else equal), a wage cut will result in $W_i(Z, R_i(Z)) - U_i(Z) < 0$ and thus the worker will quit. ■

Proposition 10 *If shocks to γ are purely transitory and the cash-flow constraint is binding, the worker's reservation productivity threshold $R_i^w(Z)$ is increasing with a transitory tightening of the constraint (i.e., a transitory decrease in γ) and the firm's reservation productivity $R_i^f(Z)$ is decreasing with a transitory tightening of the constraint.*

Proof. If shocks to γ are purely transitory (i.e., lasts for only one period), then the future values of W_i and J_i are not affected by shocks to γ. This also implies that U_i is not affected by the transitory increase, as U_i depends on future job values, but not current ones.

Assuming that the transitory shock to γ is large enough so that the cash flow constraint is binding (or that it was binding even before the transitory increase) and thus $zxa_i - w_i(Z, x) = -\gamma$, then $w_i(Z, x)$ will be lower for the period of the shock. Holding all else equal including the future wage path and future separation decisions, $\frac{dW_i(Z,x)}{dw_i} = 1$ and $\frac{dJ_i(Z,x)}{dw_i} = -1$, where w_i is the current wage, and thus $\frac{d(W_i(Z,x)-U_i(Z))}{dw_i} = 1$. Since $dw_i = d\gamma$ in the face of a binding cash-flow constraint, then $\frac{d(W_i(Z,x)-U_i(Z))}{d\gamma} = 1$ and $\frac{dJ_i(Z,x)}{d\gamma} = -1$. Implicitly differentiating the worker-separation condition (30) and the firm-separation condition (31), and using the fact that

$\frac{dW_i(Z,x)}{dx} > 0$ and $\frac{dJ_i(Z,x)}{dx} > 0$, we get

$$\frac{dR^w(Z)}{d\gamma} = -\frac{\frac{dW_i(Z,R^w(Z))}{d\gamma}}{\frac{dW_i(Z,x)}{dx}} = -\frac{1}{\frac{dW_i(Z,x)}{dx}} < 0$$

$$\frac{dR^f(Z)}{d\gamma} = -\frac{\frac{dJ_i(Z,R^f(Z))}{d\gamma}}{\frac{dJ_i(Z,x)}{dx}} = \frac{1}{\frac{dJ_i(Z,x)}{dx}} > 0.$$

In words, a tightening of the cash-flow constraint (i.e., a decrease of γ), leads to an increase in the reservation productivity threshold for the worker and a decrease in the reservation productivity threshold for the firm. ■

Corollary 11 *If shocks to γ are purely transitory, then $R^w(Z) \geq R^f(Z)$ at all times.*

Proof. The efficient-separation condition implies that $W_i(Z, R_i(Z)) - U_i(Z) = J_i(Z, R_i(Z)) = 0$, and thus if the cash-flow constraint is not binding in state Z, then $R_i^w(Z) = R_i^f(Z) = R_i(Z)$. Now consider a sufficiently large transitory shocks to γ such that the cash-flow constraint becomes binding, then the proposition above implies that $\frac{dR^w(Z)}{d\gamma} > 0$ and that $\frac{dR^f(Z)}{d\gamma} < 0$. Therefore, $R^w(Z) > R^f(Z)$ if the cash-flow constraint is binding and $R^w(Z) = R^f(Z) = R_i(Z)$ otherwise. ■

Note that the proposition above should also apply to the case of persistent shocks to γ. While persistent shocks to γ will also affect future values of W_i and J_i and thus the current U_i, the effect of the shock on U_i is smaller than the effect on current W_i because W_i depends both on current and future values of γ, whereas U_i is only affected indirectly through future values of γ.

The following aims at proving that at the efficient-separation threshold $R_i(Z)$, cash flows are more negative for high-ability workers, which implies that matches with these workers are more sensitive to cash-flow constraint shocks. While it is relatively easy to prove this for the case where the flow value of unemployment is proportional to worker productivity a_i, I could prove the result for the more general case where b_i is not proportional to a_i only for the stationary economy and where $\alpha = 0$ and $\rho_x = 0$.

Proposition 12 *In the model without binding cash-flow constraints, if $b_i = ba_i$ and $f(\theta_{low}) = f(\theta_{high}) = f(\theta)$, then for any (Z, x) the surplus of the worker-firm match is proportional to worker productivity a_i.*

Proof. From the proposition above, we know that the cash flow at the reservation match productivity level depends on the firm's discounted future expected share of the surplus. So if the firm's expected surplus share is higher for high-ability workers, then cash flows are more negative at $R_i(Z)$. Let us define $\tilde{S}_i(Z,x) = \frac{S_i(Z,x)}{a_i}$, then

$$\begin{aligned}\tilde{S}_i(Z,x) &= zx - \frac{b_i}{a_i} + \beta E\left[\max\left\{\tilde{S}_i(Z',x'),0\right\}\middle| Z,x\right] \\ &\quad -\beta f_i(\theta)\alpha E\left[\max\left\{\tilde{S}_i(Z',\bar{x}),0\right\}\middle| Z\right],\end{aligned}$$

and if $b_i = ba_i$ and $f(\theta_{low}) = f(\theta_{high}) = f(\theta)$, then for all Z and x,

$$\begin{aligned}\tilde{S}_i(Z,x) &= zx - b + \beta E\left[\max\left\{\tilde{S}_i(Z',x'),0\right\}\middle| Z,x\right] \\ &\quad -\beta f(\theta)\alpha E\left[\max\left\{\tilde{S}_i(Z',\bar{x}),0\right\}\middle| Z\right],\end{aligned}$$

which implies that $\tilde{S}_i(Z,x) = \tilde{S}(Z,x)$ is independent of ability. This implies that the surplus $S_i(Z,x) = a_i\tilde{S}(Z,x)$ is increasing proportionally to ability. ■

Proposition 13 *In the model without binding cash-flow constraints, if $b_i = ba_i$ and $c_i = ca_i$, then $f(\theta_{low}) = f(\theta_{high}) = f(\theta)$.*

Proof. The zero profit condition and Nash-bargaining imply that $\frac{c_i}{\beta E[(1-\alpha)S_i(Z',\bar{x})|Z]} = q(\theta_i)$. Given that $c_i = ca_i$ and $S_i(Z,x) = a_i\tilde{S}(Z,x)$, then the zero profit condition can be written as

$$\frac{c}{\beta E\left[(1-\alpha)\tilde{S}(Z',\bar{x})\middle| Z\right]} = q(\theta_i),$$

which implies that $q(\theta_{low}) = q(\theta_{high}) = q(\theta)$ and thus $f(\theta_{low}) = f(\theta_{high}) = f(\theta)$. ■

Corollary 14 *In the model without binding cash-flow constraints, if $b_i = ba_i$ and $c_i = ca_i$, then $R_{high}(Z) = R_{low}(Z)$.*

Proof. The efficient-separation condition states that $S_i(Z, R_i(Z)) = 0$. Therefore, if $b_i = ba_i$ and $f(\theta_{low}) = f(\theta_{high}) = f(\theta)$, $\tilde{S}(Z, R_i(Z)) = 0$, and

$$\begin{aligned}0 &= zR_i(Z) - b + \beta E\left[\max\left\{\tilde{S}(Z',x'),0\right\}\middle| Z,R_i(Z)\right] \\ &\quad -\beta f(\theta)\alpha E\left[\max\left\{\tilde{S}(Z',\bar{x}),0\right\}\middle| Z\right].\end{aligned}$$

and rearranging

$$R_i(Z) = \frac{1}{z}\left[\begin{array}{c} b - \beta E\left[\max\left\{\tilde{S}(Z',x'),0\right\}\middle| Z,R_i(Z)\right] \\ +\beta f(\theta)\alpha E\left[\max\left\{\tilde{S}(Z',\bar{x}),0\right\}\middle| Z\right]\end{array}\right].$$

Assuming that the process of match-specific productivity is the same for both types of workers and thus the conditional densities of future x', $f(x'|x)$, is the same for both types of workers, the right-hand side of the equation above is decreasing in $R_i(Z)$ (because of serial correlation of x, a marginal increase in $R_i(Z)$ increases the conditional density of future x above $R_i(Z)$, i.e. $\frac{df(x'|R_i)}{dR_i} > 0$ for all $x > R_i$). Given that the left-hand side is increasing in $R_i(Z)$, the equation above implies that $R_i(Z)$ is unique and thus independent of a_i. ■

Corollary 15 *In the model without binding cash-flow constraints, if $b_i = ba_i$ and $c_i = ca_i$, then cash flows at the efficient separation threshold $R_i(Z)$ are negative and proportional to worker productivity a_i.*

Proof. If $b_i = ba_i$ and $c_i = ca_i$, then $R_{low}(Z) = R_{high}(Z) = R(Z)$, and thus

$$\begin{aligned} CF_i(Z, R(Z)) &= -\beta E\left[\max\left\{(1-\alpha)S_i(Z', x'), 0\right\} \,\middle|\, Z, R(Z)\right] \\ &= -a_i\beta E\left[\max\left\{(1-\alpha)\tilde{S}(Z', x'), 0\right\} \,\middle|\, Z, R(Z)\right]. \end{aligned}$$

■

H.3 Robustness checks

Table H shows robustness checks for the model with cash-flow constraints:

- Panels A.2, A.3 and A.4 in Table H show simulation results for various sizes of the shock. Interestingly, the compositional effect is largest for intermediate values of the shock (and larger than in the data). The reason is that small shocks affect mostly marginal worker-firm matches, i.e., matches with productivity close to the efficient-separation threshold. As shown above, marginal matches with high-ability workers produce more negative cash-flows and thus they are the first ones to go, whereas larger cash-flow constraint shocks also affect low-ability type workers (in the extreme, where $\gamma \to -\infty$, all matches are dissolved).

- Panels A.5 and B.1 in Table H show that the compositional effects of the cash-flow constraint shocks are sensitive to parameters, such as σ_ε and ρ_x. This is to be expected, as these parameters affect the extent of labor hoarding in the model in the absence of constraints (i.e., how negative the cash flow is at the efficient-separation threshold). More precisely, with lower σ_ε and ρ_x, the overall variance of match productivities and thus future match surpluses is smaller, and thus the firm is less willing to tolerate current negative cash flows, since the conditional mean of future match surpluses is smaller (i.e., conditional on being at the reservation productivity threshold). Therefore, the cash-flow constraint is less binding in the bad state and the compositional effects of these shocks are weaker.

- Panel B.2 in Table H shows that the results are not sensitive to assuming that the average length of a recession is 11.1 months and the average length of an expansion is 59.5 months (as in the U.S. postwar era).

- Panels B.3 and B.4 in Table H show simulation results where the cash-flow constraint is set in proportion to worker-specific ability a_i, i.e. $\gamma_i = \gamma a_i$. The results show that this model version produces substantial compositional effects for various magnitudes of the shock.[27] The reason is that there is a non-proportionality in the model as flow values of unemployment b_i are not fully proportional to worker ability a_i. As explained in the paper, the b_is are calibrated internally and chosen so as to match the group-specific average separation rates in the data. Overall, these 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.

- Panel B.5 in Table H shows results where the cash-flow constraint is constant *but binding* in the good and bad aggregate state. Aggregate productivity shocks are the only source of aggregate shocks in this calibration. The results illustrate that constant cash-flow constraints cannot explain the patterns in the data, as the results are nearly identical to the baseline model with aggregate productivity shocks only (see Panel A.1 in Table G.1).

H.4 Further discussion and further results

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 with the cash-flow constraint model may be that, in the model, firms are small in the sense that they only have one employee. It may be argued that, if firms

[27] Note that the size of the shock for the high-ability worker ($\gamma_i = \gamma a_i = 0.071$) in Panel B.3 of Table H is close to the size of the shock in the baseline shown in Panel A.1 of Table H.

had more than one worker, the above mechanism would produce different results because the cash-flow constraint would be operating at the firm and not at the match level. In particular, high-ability workers generate a higher surplus for the firm (because of high expected future productivity) and thus, the firm might prefer to lay off low-ability workers in order to keep its high-ability workers. Notice, however, that in a multi-worker firm, each worker-firm relationship has a shadow value of relaxing the cash-flow constraint today and in future states where it is binding.

To make this point clearer, in the model without cash-flow constraints, I simulated the average cash flows generated by a match at the reservation match productivity threshold over the course of a recession (Figure 4 in this Appendix). I call workers in these matches "marginal" as the match productivity is at the reservation match productivity and thus these are the workers that the firm will let go first.

The Figure 4 shows that the cash flow at the time since $x = R$, is dis-proportionally negative for high-ability workers. While the ratio of worker ability is a_{high}/a_{low}= 1.425/0.575 = 2.48, as explained in the calibration of the baseline model, the ratio of cash flows at the efficient-separation threshold R_i between high- and low-ability workers is 2.89. This non-proportionality arises due to imperfect indexation of flow-values of unemployment b to worker ability a. However, this is not sufficient to argue that the results will carry over to a model with multi-worker firms, as the efficient-separation condition implies that, if the ratio of cash flows at the efficient-separation threshold R_i is 2.89, then the ratio of discounted future expected surpluses is also 2.89. In other words, this simply suggests that the benefits and costs of firing a marginal high-ability worker are 2.89 times higher compared to firing a marginal low-ability worker. Therefore, one may argue that the multi-worker firm should be indifferent between firing 100 marginal high-ability workers and firing 289 marginal low-ability workers.

However, in the presence of serially correlated match-productivity shocks, this neglects the additional benefit of firing marginal high-ability workers for relaxing cash-flow constraints in future states where these constraints are still binding. Because of the non-proportionality in the model due to imperfect indexation of flow values of unemployment b to worker ability a, reservation match productivities are lower level for high-ability workers. Therefore, in the presence of serially correlated match-productivity shocks, as shown in Figure 4 here, cash flows for high-ability workers *remain* much more negative over the course of a recession of average length (24 months) or even for shorter recessions:

1. It takes longer, on average, for marginal high-ability worker-firm matches to return to profitability (i.e., positive cash flows): 33 months for marginal high-ability workers vs. 25 months for marginal low-ability workers.

2. Over the course of a recession of average length (24 months), average cumulative cash

flows are 3.51 times more negative for high-ability workers compared to low-ability workers compared to a ratio of 2.89 of current cash flows.

How is it possible that firms are willing to take so much more cumulative losses for high-ability workers? The non-proportionality of b to a is part of the answer. A related reason is that matches with high-ability workers have a lower average separation rate and, therefore, the effective discount factor of the match (i.e., the discount factor times the survival probability) is much higher. In other words, match surpluses far in the future have a higher discounted value and thus firms are willing to accept longer periods of negative cash-flows for high-ability workers.

In terms of the numerical example given above, this observation suggests strongly that firing 100 marginal high-ability workers relaxes cash-flow constraints more at points in the near future and thus the firm would prefer firing 100 marginal high-ability workers to firing 289 marginal low-ability workers. In other words, firing marginal high-ability workers has the advantage that the firm may not have to fire additional workers in the near future. In addition, if there are small fixed firing costs per worker, then the firm would prefer getting rid off marginal high-ability workers, even if cash flows were fully proportional to ability.

Of course, it would be best to set up a multi-worker firm model to prove these suggestive results formally and/or simulate such a model to analyze the effect of firm-level cash-flow constraints on the firm's firing decision. However, as pointed out in the paper, it is very challenging to set up such a model, in particular, because of potential interactions of the wage bargaining between the different types of workers as well as interactions of the wage bargaining with the cash-flow constraint and the separation decision. This important extension is thus left for future work.

Figure 4: *Cash flows for marginal matches over the course of a recession (in the baseline model without cash flow constraints)*

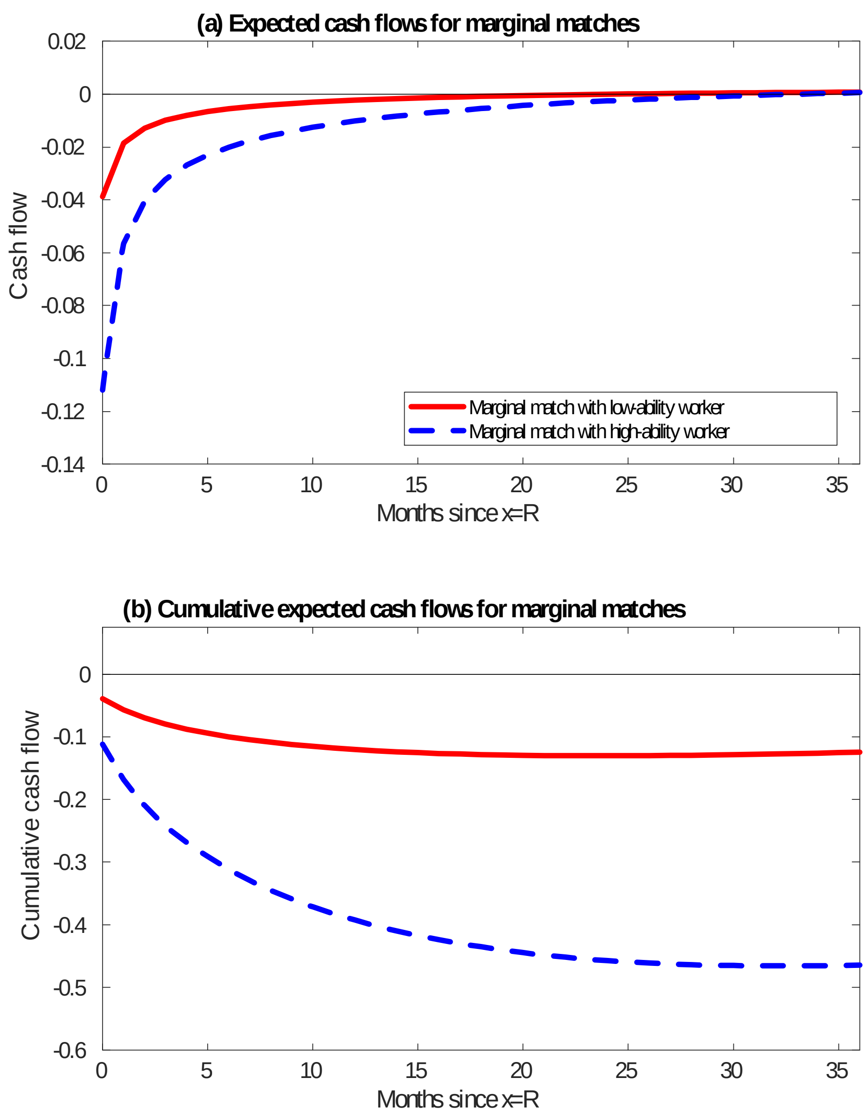


TABLE H. ROBUSTNESS CHECKS FOR THE MODEL WITH CREDIT-CONSTRAINT SHOCKS

Statistic:	**A.1** $\gamma(b)=0.08$ (Baseline)		**A.2** $\gamma(b)=0.05$		**A.3** $\gamma(b)=0.02$		**A.4** $\gamma(b)=0.00$		**A.5** $\gamma(b)=0.05$, $\sigma_\varepsilon=0.015$, $\alpha=0.1$	
Cyclicality of aggregate										
… log pre-displacement wage	4.13		8.73		4.04		1.85		6.56	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.61	1.51	0.45	2.26	0.88	1.76	1.22	1.52	0.52	2.16
… log job finding rates	-0.35	-0.16	-0.22	-0.09	-0.10	0.00	0.09	0.04	-0.24	-0.08
… log unemployment rates	0.77	1.43	0.50	1.96	0.78	1.43	0.91	1.18	0.65	1.88
… log reservation productivities	0.03	0.07	0.02	0.09	0.04	0.07	0.05	0.06	0.01	0.05
Aggregate time-series statistics:										
Std(log separation rate)	0.092		0.144		0.307		0.532		0.486	
Std(log job finding rate)	0.022		0.021		0.015		0.026		0.086	
Std(log unemployment rate)	0.068		0.098		0.194		0.288		0.383	
Cross-sectional statistics:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
Std(log wage changes)	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.00	0.01
AR(1) coefficient of log wages	0.98	0.97	0.98	0.97	0.98	0.97	0.97	0.97	0.98	0.92
Group-specific parameters:										
b_i / a_i	0.81	0.49	0.81	0.43	0.77	0.38	0.71	0.35	1.00	0.89
$\sigma_{\varepsilon,i}$	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.015	0.015
c_i	0.14	0.76	0.14	0.83	0.16	0.92	0.21	1.01	0.14	1.36

Statistic:	**B.1** $\gamma(b)=0.05$, $\rho_x=0.9$		**B.2** $\gamma(b)=0.08$, $p_{gb}=1/11.1$, $p_{bg}=1/59.5$		**B.3** γ shocks proportional to a_i ($\gamma_i(b)=0.05$)		**B.4** γ shocks proportional to a_i ($\gamma_i(b)=0.00$)		**B.5** Constant γ ($\gamma(b)=\gamma(g)=0.00$)	
Cyclicality of aggregate										
… log pre-displacement wage	4.45		4.33		1.80		1.85		-1.14	
Cyclicality of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.65	1.51	0.65	1.52	0.96	1.35	1.22	1.52	1.31	1.02
… log job finding rates	-0.26	-0.18	-0.30	-0.14	-0.20	-0.10	0.09	0.04	-0.15	-0.08
… log unemployment rates	0.76	1.47	0.74	1.47	0.90	1.18	0.91	1.18	1.08	0.85
… log reservation productivities	0.02	0.04	0.03	0.06	0.04	0.05	0.05	0.06	0.05	0.04
Aggregate time-series statistics:										
Std(log separation rate)	0.245		0.079		0.153		0.532		0.061	
Std(log job finding rate)	0.050		0.015		0.020		0.026		0.006	
Std(log unemployment rate)	0.199		0.055		0.101		0.288		0.037	
Cross-sectional statistics:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
Std(log wage changes)	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.06	0.06
AR(1) coefficient of log wages	0.89	0.88	0.98	0.97	0.98	0.97	0.97	0.97	0.97	0.96
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.90	0.84	0.82	0.51	0.79	0.48	0.71	0.35	0.65	0.21
$\sigma_{\varepsilon,i}$	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
c_i	0.06	0.23	0.14	0.73	0.15	0.78	0.21	1.01	0.28	1.29

Notes: See Table 4 for details.

Appendix I. A search-matching model with non-segmented labor markets

In this appendix, I first set up a model with non-segmented labor markets and exogenous separations and then set up a model with non-segmented labor markets and endogenous separations. The reason why I first set up a model with exogenous separations is that it allows me to directly calibrate the cyclicality of the separation rates as in the data and to explore the implications of my findings for aggregate fluctuations of the job finding rate. In both models, the results are computed for the stationary equilibrium with no aggregate shocks.

I.1 Non-segmented labor markets and exogenous separations

This appendix sets up a model with non-segmented labor markets and exogenous separations, which is closely related to the model by Pries (2008). This is a special case of the baseline model set up in the paper, with no match-specific shocks x (i.e., $\sigma_\varepsilon = 0$) and where the separation shock λ_i is potentially idiosyncratic to the worker and thus bears a subscript i.

If search on the firm side is not directed to a particular worker type, then there is only one aggregate matching function:

$$M = \kappa u^\eta v^{1-\eta}. \tag{36}$$

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

Value functions, wage setting and equilibrium. The value functions of the unemployed and employed worker of type i are:

$$\begin{aligned} U_i(Z) &= b_i + \beta E\left[(1-f(\theta_i))U_i(Z') + f(\theta_i)W_i(Z') \middle| Z\right] && (37) \\ W_i(Z) &= w_i(Z) + \beta E\left[(1-\lambda_i)W_i(Z') + \lambda_i U_i(Z') \middle| Z\right]. && (38) \end{aligned}$$

The value for the filled vacancy with worker of type i is:

$$J_i(Z) = za_i - w_i(Z) + \beta E\left[(1-\lambda)J_i(Z') + \lambda V_i(Z') \middle| Z\right]. \tag{39}$$

The value for the unfilled vacancy is:

$$
\begin{aligned}
V(Z) &= -c + \beta E[(1-q(\theta))V(Z') \\
&\quad + q(\theta)\left(\frac{u_{low}}{u_{low}+u_{high}}J_l(Z') + \frac{u_{high}}{u_{low}+u_{high}}J_h(Z')\right)\Bigg| Z],
\end{aligned} \tag{40}
$$

where the important difference to the model with segmented labor markets is that the value of the vacancy is now independent of type, as firms post vacancies for all types of workers.[28] This implies that the value of posting a vacancy depends on the share of the low-ability types in the pool of unemployed, $\pi = \frac{u_{low}}{u_{low}+u_{high}}$. The law of motion for the unemployment rate u_i for workers of type i is:

$$
u_i' = u_i(1 - f(\theta(Z))) + \lambda_i'(1-u_i), \tag{41}
$$

and the aggregate state space in this economy is $Z = [z, \lambda_{low}, \lambda_{high}, u_{low}, u_{high}]$. The group-specific unemployment rates u_i are part of the aggregate state space, as they help to predict the future composition of the pool of unemployed, which in turn influences the Nash-bargained wage and thus firms' vacancy posting decision.

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

$$
w_i(Z) = \arg\max_{w_i}(W_i(Z) - U_i(Z))^{\alpha}(J_i(Z) - V(Z))^{1-\alpha} \tag{42}
$$

where α is the bargaining share of the worker.

Definition 16 *A search equilibrium with non-segmented labor markets and exogenous separations is defined as the wage schedules $w_i(Z)$, the labor market tightness $\theta(Z)$, the unemployment rates u_i, and the value functions $U_i(Z)$,$W_i(Z)$,$V(Z)$ and $J_i(Z)$, that satisfy the Nash-bargaining solution (42) for each worker type i, the zero-profit condition $V(Z) = 0$, the law of motion (41) for each worker type i, and the value functions (37), (38) and (39) for each worker type i, and the value function (40).*

Calibration and results. The calibration follows the baseline calibration in the paper. The only difference is that I need to calibrate the exogenous separation rates. Note also that I set the values for b_i to the same values as in the baseline calibration in the paper (I no longer calibrate these parameters internally, as separations are now exogenous).

Table I.1 shows steady state elasticities with respect to z, for four different types of calibrations:

[28] Equations (37) and (40) implicitly assume that the value of the new match is greater than the value of the outside option, but note that this always holds for both types of workers and for all calibrations considered in this Appendix.

- Panel A.1 in Table I.1 shows results for a calibration where the λ_i shocks are assumed to be proportional to the average group-specific separation rate, i.e., $\lambda_i = \lambda E(s_i)$, where λ is set to match the differences in the aggregate separation rate in the good and the bad state in the other calibrations below. This calibration serves as a benchmark, for the composition of the pool of unemployed is constant over the cycle (to verify this, the table reports the steady state elasticities of *group-specific* separation and job finding rates, which are identical for both groups in this calibration). The results show that the steady state elasticity of the *aggregate* job finding rate is about 1.5, which is substantially below its cyclical volatility in the data. Shimer (2005), e.g., reports a standard deviation of $\ln(z)$ of 0.02 and a standard deviation of $\ln(f)$ of 0.12. The ratio of the two is 6, which is substantially higher than the steady state elasticity reported here.

- Panel A.2 in Table I.1 follows the calibration strategy of Pries (2008), who assumed that separations of low-ability types are perfectly negatively correlated with z, whereas separations of high-ability workers are assumed to be constant over the cycle. The results indicate that the compositional changes in the pool of unemployed towards *low*-ability workers in recessions amplify fluctuations in the job finding rate by a factor 1.8 relative to the baseline economy with no compositional changes (the results in Panel A.1). This is in line with Pries' result which found an amplification of productivity shocks by a factor of between 2.3 and 4.3.[29]

- Panel A.3 in Table I.1 shows results for an economy where the separation shocks are calibrated to the CPS ORG data. To that purpose, I divide my sample in the CPS ORG data into periods where the monthly aggregate unemployment rate is above its HP-trend and periods where it is below its HP-trend, and compute the average monthly separation rate for both samples for low- and high-wage workers. I directly use these values to calibrate the λ_i shocks in this calibration, i.e. I set:

$$\begin{aligned}
\lambda_{low,g} &= 0.0138 \\
\lambda_{low,b} &= 0.0152 \\
\lambda_{high,g} &= 0.0067 \\
\lambda_{high,b} &= 0.0085
\end{aligned}$$

  where b stands for the bad aggregate state and g stands for the good aggregate state. The exogenous separation shocks are assumed to be perfectly correlated with the aggre-

[29]The difference between Pries' and my results can be explained by slightly different calibrated values of b_i. Note also that Pries simulates the fully dynamic version of the model, whereas I only provide steady state elasticities here.

gate productivity shock z. Interestingly, this is close to the values in the model with indiscriminate separation shocks where separations increase exogenously by 0.0016 between the good and bad state[30], whereas here the separation rate increases by 0.0018 for high-ability workers and by 0.0014 for low-ability workers. The results indicate that the compositional changes lead to a substantial dampening of the aggregate job finding rate by a factor of 2.0 relative to the baseline with no compositional effects shown in Panel A.1 of Table I.1.

- Panels B.1, B.2 and B.3 peform the same exercise for a calibration where the flow values of unemployment are set to a lower level ($\frac{b_{low}}{a_{low}} = 0.7$ and $\frac{b_{high}}{a_{high}} = 0.25$). The exercise shows that the compositional changes in Panel B.3 lead to an even more substantial dampening of the aggregate job finding rate by a factor of 3.6 relative to the baseline with no compositional effects shown in Panel B.1 of Table I.1. The reason is that in this calibration flow values are even less proportional to ability and thus high-ability workers produces disproportionality high surpluses. Therefore, firms have even more an incentive to post vacancies in periods of recessions when the composition of the pool of unemployed moves towards the high types.

[30] I.e., for the calibration that matches the cyclicality of the mass layoff rate (see Panel D of Table 5 in the paper).

TABLE I.1 MAIN RESULTS FOR THE MODEL WITH NON-SEGMENTED LABOR MARKETS AND EXOGENOUS SEPARATION SHOCKS

Statistic:	***A.1*** *Shocks proportional to $E(s_i)$*		***A.2*** *Shocks to low-ability workers only*		***A.3*** *Shocks calibrated to match CPS ORG data*		***B.1*** *Shocks proportional to $E(s_i)$*		***B.2*** *Shocks to low-ability workers only*		***B.3*** *Shocks calibrated to match CPS ORG data*	
S.s. elasticity w.r.t. z of												
… log separation rate	-3.39		-3.31		-3.39		-3.39		-3.31		-3.39	
… log job finding rate	1.52		2.74		0.76		1.03		2.23		0.29	
… log unemployment rate	-4.48		-5.29		-3.90		-4.11		-4.93		-3.52	
S.s. elasticity w.r.t. z of group-specific	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	-3.4	-3.4	-5.0	0.0	-2.3	-5.3	-3.4	-3.4	-5.0	0.0	-2.3	-5.3
… log job finding rates	1.5	1.5	2.7	2.7	0.8	0.8	1.0	1.0	2.2	2.2	0.3	0.3
… log unemployment rates	-4.4	-4.5	-6.7	-2.4	-2.8	-5.8	-4.1	-4.2	-6.4	-2.0	-2.5	-5.4
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.80	0.50	0.80	0.50	0.80	0.50	0.70	0.25	0.70	0.25	0.70	0.25
c_i	0.30	0.30	0.30	0.30	0.30	0.30	0.42	0.42	0.42	0.42	0.42	0.42

I.2 Non-segmented labor markets and endogenous separations

This section sets up a model with non-segmented labor markets and endogenous separations. The model here allows for aggregate labor productivity shocks z, indiscriminate separation shocks λ and cash-flow constraint shocks γ. Therefore, the model is closely related to the model described in Appendix E, except that labor markets are not segmented and thus firms do not direct their search towards a worker of a particular type. If search on the firm side is not directed to a particular worker type, then there is only one aggregate matching function:

$$M = \kappa u^{\eta} v^{1-\eta}. \tag{43}$$

Value functions, wage setting and equilibrium. The value functions $U_i(Z)$, $W_i(Z,x)$ and $J_i(Z,x)$ are isomorphic to the value functions (26), (27) and (29) shown in Appendix E and thus are not shown here. Similarly, the cash-flow constraint and the worker- and firm-separation conditions are identical and thus not shown here.

The value of the unfilled vacancy is:

$$\begin{aligned} V(Z) \quad = \quad & -c + \beta E[(1-q(\theta))V(Z') \\ & + q(\theta)\left(\frac{u_{low}}{u_{low}+u_{high}} J_l(Z',\bar{x}) + \frac{u_{high}}{u_{low}+u_{high}} J_h(Z',\bar{x})\right) \Bigg| Z], \end{aligned} \tag{44}$$

where the important difference to the model with segmented labor markets is that the value of the vacancy is now independent of type, as firms post vacancies for all types of workers.[31] This implies that the value of posting a vacancy depends on the share of the low-ability types in the pool of unemployed, $\pi = \frac{u_{low}}{u_{low}+u_{high}}$.

The law of motion for the unemployment rate u_i for workers of type i is:

$$u_i' = u_i(1 - f(\theta(Z))) + s_i'(1-u_i), \tag{45}$$

where

$$s_i' = \lambda' + \int s_i'(x) g_i(x) dx.$$

and where $g_i(.)$ is the probability density function of the distribution of match-specific productivities for workers of type i and where $s_i'(x) = \Pr\left[x' < \max\left\{R_i^f, R_i^w\right\} |x\right]$ is the separation rate for a worker with match-specific productivity x.

[31] Equation (44) implicitly assumes that the value of the new match is greater than the value of the outside option, but note that this always holds for both types of workers and for all calibrations considered in this Appendix.

The law of motion for the distribution match-specific productivities x for worker-type i can be written as

$$G_i' = H_i(G_i, G_{-i}, u_i, u_{-i}, z, \lambda, \gamma, z', \lambda', \gamma'), \tag{46}$$

where G_i is the cumulative density function of x for workers of type i, where G_{-i} is the cumulative density function of x for workers of the other type, where u_i is the unemployment rate for workers of type i and where u_{-i} is the unemployment rate for workers of the other type. H_i is a function, which depends on:

- the parameters of the process of match-specific productivities (σ_ε and ρ_x) and the reservation productivities $R_i^{z\prime}$ and $R_i^{f\prime}$, which in turn depend on the future state of aggregate shocks z, λ and γ, and
- the number of newly employed workers in the next period and thus the current unemployment rate u_i and the current job finding rate $f(\theta(Z))$, which in turn depends on the current states of the aggregate shocks z, λ and γ, as well as all objects that determine current and future values of $\pi = \frac{u_{low}}{u_{low}+u_{high}}\,(G_i, G_{-i}, u_i, u_{-i})$.[32]

The aggregate state is described by $Z = [G_{low}, G_{high}, u_{low}, u_{high}, z, \lambda, \gamma]$.

Definition 17 *A search equilibrium with non-segmented labor markets, endogenous separations and cash-flow constraints is defined as the worker-reservation productivities $R_i^w(Z)$, the firm-reservation productivities $R_i^f(Z)$, the wage schedules $w_i(Z, x)$, the Nash-bargaining wage schedules $w_i^{NB}(Z, x)$, the labor market tightness $\theta(Z)$, the unemployment rates u_i, the distributions of match-specific productivities G_i, and the value functions $U_i(Z)$,$W_i(Z, x)$,$V(Z)$ and $J_i(Z, x)$ that satisfy the worker-separation condition (30) for each worker type i, the firm-separation condition (31) for each worker type i, the wage schedule (33) for each worker type i, the Nash-bargaining solution (34) for each worker type i, the zero-profit condition $V(Z) = 0$, the law of motion for u_i (45) for each worker type i, the law of motion for G_i (46) for each worker type i, and the value functions (26), (27) and (29) for each worker type i, and the value function (44).*

It is generally not possible to solve a model with a highly dimensional state space such as with the distribution of worker types across match productivities. For this reason, I only report comparative statitics for the model with non-segmented labor markets because in the steady state, the distribution of worker types is constant across time. I leave it to future work to compute an approximate dynamic equilibrium with a limited set of aggregate state variables similar to Krusell and Smith's (1998) method in models with heterogeneity in asset holdings.

[32] π affects firms' incentives to post vacancies and thus the job finding rate, which in turn affects the value of unemployment. Therefore, future values of π determine future job finding rates, which in turn affect current values of U_i, W_i and J_i and thus the current wage and the current job finding rate.

Calibration and results. Table I.2 reports the results for the model with segmented labor markets and the model with non-segmented labor markets for four different calibrations, which correspond to the main calibrations reported in Table 4 in the paper. The only difference is that I assumed that for Panel D the cash-flow constraint parameter $\gamma = 0.05$ instead of 0.08 because, for $\gamma = 0.08$, the constraint was not binding in the stationary economy with no aggregate shocks.

The results suggest that the results in terms of the compositional effects do not differ much between the model with segmented and the model with non-segmented shocks, and if anything tend to reinforce the conclusions from the paper.[33]

Note also that the model with non-segmented shocks tends to dampen aggregate productivity shocks in the face of compositional changes in the pool of unemployed towards the high-ability workers in recessions. To see this, compare the steady state elasticity of the aggregate job finding rate for models of segmented and non-segmented labor markets in Panels C and D in Table I.2. See also the results in Appendix I.1 where separation rates are set exogenously and set to match exactly the data.

[33] The magnitude of the effects for the model with segmented labor markets is quite different from the results of the dynamic version of the model reported in Table 4 of the paper. The reason is that the reservation match productivities depend on the persistence of aggregate productivity shocks.

TABLE I.2 COMPARATIVE STATICS IN MODELS WITH SEGMENTED AND NON-SEGMENTED LABOR MARKETS

	A. Baseline model				***B. Alternative calibration***			
Statistic:	*Segmented labor markets*		*Non-segmented labor markets*		*Segmented labor markets*		*Non-segmented labor markets*	
S.s. elasticity of aggregate (w.r.t. u)								
… log pre-displacement wage	-4.45		-4.50		0.97		0.99	
S.s. elasticity of group-specific (w.r.t. log(u))	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.37	0.01	0.56	-0.34	0.24	0.34	0.24	0.37
… log job finding rates	-1.07	-0.50	-0.86	-0.86	-0.82	-0.84	-0.82	-0.82
… log unemployment rates	1.27	0.48	1.27	0.47	0.95	1.09	0.95	1.09
S.s. elasticity of aggregate (w.r.t. z)								
… log separation rate	-0.5		-0.5		-0.6		-0.6	
… log job finding rate	1.8		1.7		1.7		1.7	
… log unemployment rate	-2.1		-2.0		-2.0		-2.0	
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.81	0.52	0.81	0.52	0.71	0.71	0.71	0.71
$\sigma_{\varepsilon,i}$	0.028	0.028	0.028	0.028	0.037	0.016	0.037	0.016
c_i	0.13	0.71	0.33	0.33	0.18	0.43	0.26	0.26

	C. Indiscriminate separation shocks				***D. Credit-constraint shocks ($\gamma(b)$= 0.05)***			
Statistic:	*Segmented labor markets*		*Non-segmented labor markets*		*Segmented labor markets*		*Non-segmented labor markets*	
S.s. elasticity of aggregate (w.r.t. u)								
… log pre-displacement wage	-0.37		0.22		5.16		6.42	
S.s. elasticity of group-specific (w.r.t. log(u))	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
… log separation rates	0.58	0.67	0.75	0.63	0.21	1.33	0.59	1.55
… log job finding rates	-0.60	-0.25	-0.36	-0.36	-0.61	-0.25	-0.11	-0.11
… log unemployment rates	1.06	0.88	1.03	0.94	0.72	1.50	0.66	1.60
S.s. elasticity of aggregate (w.r.t. z)								
… log separation rate	-1.6		-1.8		-2.3		-3.3	
… log job finding rate	1.2		0.9		1.8		0.4	
… log unemployment rate	-2.6		-2.5		-3.7		-3.5	
Group-specific parameters:	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}	a_{low}	a_{high}
b_i / a_i	0.66	0.10	0.66	0.10	0.81	0.45	0.81	0.45
$\sigma_{\varepsilon,i}$	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
c_i	0.21	1.25	0.57	0.57	0.13	0.80	0.37	0.37

Appendix J. Implications for the welfare costs of business cycles

This appendix explores the implications of the empirical findings of the paper for the welfare costs of business cycles. To that purpose, I set up a simple reduced-form model of unemployment where I calibrate directly the cyclical properties of job separation, job finding and consumption for low- and high-ability type of workers.

J.1 Value functions

The value of the unemployed and employed workers of type i are:

$$\begin{aligned} U_i(z) &= u(c_i^u(z)) + \beta E\left[(1 - f_i(z))U_i(z') + f_i(z)W_i(z')|\, z\right] && (47) \\ W_i(z) &= u(c_i^e(z)) + \beta E\left[(1 - \lambda_i(z))W_i(z') + \lambda_i(z)U_i(z')|\, z\right], && (48) \end{aligned}$$

where $z = [g(ood), b(ad)]$ is the aggregate state, $u(.)$ is the flow utility function, $c_i^u(z)$ is consumption while unemployed for workers of type $i = [low, high]$ in aggregate state z, $f_i(z)$ is the job finding rate for workers of type i in aggregate state z and $\lambda_i(z)$ is the separation rate for workers of type i in aggregate state z.

J.2 Computing the welfare costs of business cycles

To measure the welfare costs of business cycles, I closely follow Krusell and Smith (1999) in the sense that I apply the "integration principle", which eliminates the idiosyncratic risk that is correlated with the aggregate risk. While this approach is straight-forward for a normally distributed random variable, this turns out to be rather complex in the case of a two-state markov process of labor market transitions. I do not show the details here, but I closely follow the online appendix of Krusell et al. (2009).

The welfare gains of eliminating business cycles for worker of type i in labor market state $s = \{e, u\}$ are measured in the traditional way as the percent increase in per-period consumption, $\varkappa_{is}$, that makes an individual equally well off in an economy with business cycles compared to an economy without business cycles. As shown in the online Appendix of Krusell et al. (2009), in the case of log utility this can be written as

$$\varkappa_{is} = \exp\left((1 - \beta)\left(\tilde{V}_{is} - V_{is}\right)\right) - 1, \qquad (49)$$

where V_{is} is the expected present discounted value of utility in the economy with business cycles and $\tilde{V}_{is}$ is the expected present discounted value of utility in the economy without business cycles, and β is the discount factor.[34]

[34] Note that in contrast to Krusell at al. (2009), I assume here that the discount factor is not subject to

J.3 Calibration

As in the baseline calibration of the paper, the model frequency is monthly and thus I set $\beta = 0.9966$ and the aggregate transition probabilities to $\pi_{bg} = \pi_{gb} = 1/24$, which implies an average duration of recessions and expansions of two years. As is standard in this literature, I assume log utility, which simplifies the computation as one can use the formula (49) but is likely to understate the welfare costs if one believes the coefficient of relative risk aversion to be above one.

While the literature has focused on models with saving-consumption decisions to analyze the welfare implications of business cycles, I directly calibrate here the consumption of employed and unemployed workers based on evidence on the consumption response to unemployment and unemployment duration. This considerably simplifies the analysis, and I view this exercise a reasonable first step to explore the implications of my findings for the welfare costs of business cycles, with some obvious caveats: First, individuals facing different labor market transition processes make different consumption choices. In particular, individuals facing more risk should hold more precautionary savings, and thus contrasting any two regimes with different processes for labor market transitions will overstate the difference in the welfare costs of business cycles as this does not take into account the endogenous response of savings and consumption. The second limitation is that this does not take into account that the welfare costs are likely to be born disproportionally by constrained agents who cannot borrow (see Krusell at al., 2009) and thus the results understate the welfare costs of business cycles, even when allowing for different labor market states.

Having said this, I calibrate the following values for the consumption levels:

- The average consumption of the low-ability employed is set to 0.575 and the average consumption of the employed for high-abilty types is set to 1.425, which correspond to the worker-specific ability parameters in the calibration of the baseline model in the paper.
- The average consumption of the unemployed is set to 0.82 of the average consumption of the employed, which is in line with Gruber (1997). Note that the average consumption of the unemployed is not important for the results here but rather how much the consumption of the unemployed varies with the business cycles.[35]
- I assume that the consumption of the employed increases by one percent in good times and decreases by one percent in bad times. This implies that the welfare costs of business cycles in the absence of unemployment risk is about 0.005%, which is close to Lucas' (1987) estimate of the welfare costs of business cycles.

shocks.

[35] See more on that below.

- The key moment for this exercise is how much the consumption of the unemployed varies over the business cycles. The main reason why the consumption of the unemployed varies over the cycles is that unemployment duration increases in recessions, and thus unemployed workers are more likely to exhaust unemployment insurance (UI) and decumulate their savings. Gruber (1997) estimates the consumption response to UI. These estimates (column 3 of Table 1 of his paper) imply that consumption drops by 10 percent for a newly unemployed worker whose earnings are replaced by 50%, whereas consumption of an unemployed worker with no access to UI drops by about 25 percent relative to consumption while employed.[36] I thus assume here that long-term unemployed workers who have exhausted UI (i.e., those with duration of unemployment of more than 6 months) face a consumption drop of 25 percent relative to consumption while employed. Note that is likely to understate the drop in consumption of the unemployed in recessions since it purely relies on the response of consumption to UI exhaustion and ignores the effect of declining savings over the spell of unemployment on consumption.[37] I thus consider also calibrations with a larger drop in consumption for the unemployed in recessions relative to booms.

These estimates imply that in good times when the job finding rate is 0.348,[38] the average consumption of the unemployed is 0.825 *relative to* the consumption of the employed, whereas in bad times when the job finding rate is 0.285 the average consumption of the unemployed is 0.81 *relative to* the consumption of the employed. Taking into account that the ratio of consumption of the employed between bad and good times is 0.98, this implies that the ratio of consumption of the unemployed between bad and good times is 0.962.[39]

Table I shows results for two economies, one where separation shocks are calibrated in

[36]Note that I adjust these estimates to take into account the fact that they are based on the response of food consumption, which tends to be less elastic than other income categories. I thus divide Gruber's estimates by the income elasticity of food consumption (0.61) reported by Blundell, Pashardes and Weber (1993).

[37]Note, however, that the calculation is also in line with the recent paper by Kolsrud et al. (2015), which directly estimates the consumption response to unemployment duration in Sweden and finds that unemployment duration decreases nearly linearly by about 2.2 percent per month relative to pre-unemployment consumption for the first year and remains flat thereafter. I get very similar results using their estimates instead of relying on Gruber's estimates.

[38]The job finding rate for the good (bad) state is computed in similar ways as the job separation rate, by taking the average of the job finding rate in the CPS ORG data for months where the aggregate unemployment rate is below (above) its trend. See also Appendix I.1.

[39]The exact formula that was used is

$$c_i^u(z) = \left[(1-(1-f(z))^6)\frac{c_i^{us}(z)}{c_i^e(z)} + (1-f(z))^6\frac{c_i^{lu}(z)}{c_i^e(z)}\right] c_e(z)$$

where $\frac{c_i^{us}(z)}{c_i^e(z)}$ is the consumption of the short-term unemployed relative to the consumption of the employed, $\frac{c_i^{lu}(z)}{c_i^e(z)}$ is the consumption of the long-term unemployed relative to the consumption of the employed, and $f(z)$ is the monthly job finding rate.

proportion to the average separation rate for each group (implying that there is no compositional change in the pool of unemployed) and one where the separation shocks are calibrated to the CPS ORG data. The values of $\lambda_i(z)$ for the latter calibration are (see the Appendix I.1 for details):

$$\begin{aligned}
\lambda_{low}(g) &= 0.0138 \\
\lambda_{low}(b) &= 0.0152 \\
\lambda_{high}(g) &= 0.0067 \\
\lambda_{high}(b) &= 0.0085
\end{aligned}$$

whereas for the economy with proportional shocks, I assumed that $\lambda_i(z)$ increase proportionally to the average separation rate in the data, holding the increase of the aggregate separation between good and bad state the same in both calibrations.

J.4 Results and discussion

Panel A of Table J shows results for the baseline calibration where the ratio of the consumption of the unemployed between the good and the bad state is 0.962, as discussed above. The average welfare costs of business cycles are just 0.01% in this setting and do not depend on calibration of the separation shocks. The main difference between the two calibrations is that in the case of proportional shocks to the separation rate the welfare costs of business cycles are born disproportionally by the low-ability types, whereas, in the model where shocks are calibrated to the CPS ORG data the welfare costs are spread more evenly.

These result carry over to the simulation results shown in Panel B of Table J, where I allowed for a more cyclical response of the consumption of the unemployed, and where average welfare costs are close to the ones reported in Mukoyama and Sahin (2006) and Krusell et al. (2009)[40].

In Panels C and D of Table J, I allow for a calibration where high- and low-ability workers differ in their ability to self-insure against unemployment shocks. Panel C shows results where the high-ability workers suffer a larger drop in consumption during recessions than low-ability workers. In this calibration, the overall magnitude of the welfare costs of business cycles increases slightly relative to the calibration with proportional shocks. Panel D shows results where the low-ability workers suffer a larger drop in consumption during recessions than high-ability workers. In this calibration, the overall magnitude of the welfare costs of business cycles decreases slightly relative to the calibration with proportional shocks.

[40] For the latter, I refer to the baseline results where they do not allow for long-term unemployment as a third labor market state.

Overall, I conclude from this exercise that my empirical results in the paper imply that the welfare costs of business cycles are shared more equally across workers of different ability levels, compared to model calibrations with proportional separation shocks. The effect on the overall magnitude of the welfare costs of business cycles depends on the ability of low- and high-ability workers to self-insure. Mukoyama and Sahin (2006) calibrate a dynamic general equilibrium model with incomplete markets and find that high-ability workers accumulate more precautionary savings. Incorporating my empirical results into their paper thus would result in a lower overall welfare cost of business cycles.[41]

One should also note here that the magnitude of the welfare costs of business cycles considered here is relatively modest. However, Krusell et al. (2009), e.g., find that the welfare costs of business cycles are an order of magnitude higher when incorporating long-term unemployment as a third labor market state. Moreover, as shown by Krebs (2007), the welfare costs of business cycles increase substantially with higher degrees of risk aversion in a model with job displacement risk. Finally, Beaudry and Pages (2001) assume that macroeconomic stabilization policy can eliminate recessions without affecting economic expansions, which strongly increases the welfare costs of business cycles (in other words, the welfare costs of recessions are much larger than the welfare costs of business cycles). For all these reasons, using models that imply larger welfare costs of business cycles and allowing for higher degrees of risk aversion may lead to much starker differences between calibrations with proportional shocks and calibrations with non-proportional separation shocks that match the empirical results in this paper. This important work is left for future research.

[41] Note that Mukoyama and Sahin (2006) calibrate separations to increase more than proportionally for *low*-ability workers, whereas my results in the CPS ORG show that separation rates increase more than proportionally for *high*-ability workers.

TABLE J. WELFARE COSTS OF BUSINESS CYCLES FOR DIFFERENT PROCESSES OF LABOR MARKET TRANSITIONS AND CONSUMPTION

	A.		*B.*		*C.*		*D.*	
	Proportional shocks	*Shocks calibrated to CPS ORG data*	*Proportional shocks*	*Shocks calibrated to CPS ORG data*	*Proportional shocks*	*Shocks calibrated to CPS ORG data*	*Proportional shocks*	*Shocks calibrated to CPS ORG data*
Average welfare cost	0.010%	0.010%	0.054%	0.054%	0.049%	0.052%	0.063%	0.061%
Ratio of welfare costs between low- and high-ability types	1.36	1.16	1.74	1.36	0.70	0.55	4.23	3.33
Welfare costs by worker type:								
Low-ability workers								
All	0.012%	0.011%	0.069%	0.062%	0.041%	0.037%	0.103%	0.094%
Unemployed	0.013%	0.012%	0.078%	0.071%	0.045%	0.041%	0.117%	0.108%
Employed	0.012%	0.011%	0.068%	0.062%	0.040%	0.036%	0.101%	0.092%
High-ability workers								
All	0.009%	0.010%	0.040%	0.046%	0.058%	0.067%	0.024%	0.028%
Unemployed	0.010%	0.011%	0.049%	0.055%	0.073%	0.082%	0.029%	0.033%
Employed	0.009%	0.010%	0.039%	0.045%	0.057%	0.066%	0.024%	0.028%

Calibrated values of c(b)/c(g) by type of worker:

	A.	B.	C.	D.
Low-ability unemployed	0.962	0.850	0.900	0.800
High-ability unemployed	0.962	0.850	0.800	0.900
Low-ability employed	0.980	0.980	0.980	0.980
High-ability employed	0.980	0.980	0.980	0.980

Notes: Welfare costs are measured as the percent increase in consumption that makes an individual equally well off in an economy with business cycles compared to an economy without business cycles (see the text in the Appendix J for details).

Appendix K. Composition bias in the measurement of the cyclicality of statistics related to the unemployed

As argued in the introduction, the findings have potentially important implications for the measurement of the cyclicality of statistics related to the unemployed, as compositional changes in the pool may lead to biases in these estimates. This Appendix provides some additional details and argues that these biases may be of substantial magnitude. Of course, it would be best to demonstrate the presence of such a bias directly, by estimating the cyclicality of the statistic of interest and show how the estimates change when controlling for the pre-displacement wage. Unfortunately, for most applications of interest, the pre-displacement wage is not available or would restrict the size of the sample so that is too small for meaningful inference on the extent of the composition bias. For this reason, I limit the analysis here to back-of-the-envelope calculations of the *potential* magnitude of such a bias.

The extent of composition bias in the cyclicality of statistics related to the unemployed relies on two different elasticities:

1. The extent of the compositional shift over the business cycle, measured here as the change in the average log pre-displacement wage.
2. The extent to which the statistic of interest is sensitive to the pre-displacement wage. If the statistic of interest does not depend on the pre-displacement wage, then there is no composition bias as the statistic of interest does not change as a result of the compositional shift.

One can thus quantify the potential composition bias for statistic x^u based on the following formula (time subscripts are dropped for convenience):

$$bias(\frac{dx^u}{dU}) = \frac{dx^u}{d\ln w^u}\frac{d\ln w^u}{dU}$$

where $\frac{d\ln w^u}{dU}$ is the response of the pre-displacement wage to a one percentage point increase in the unemployment rate and where $\frac{dx^u}{d\ln w^u}$ is the response of the statistic of interest x^u to the pre-displacement wage.[42] $\frac{d\ln w^u}{dU}$ is the main statistic reported in Table 1 of the paper, which is 2.77 for the raw wage measure and 0.75 for the wage residual. In a typical recession, where the detrended unemployment rate increases by about 2.5 percentage points, this amounts to an increase of the average pre-displacement wage of about 7 log points or 2 log points in terms of the wage residual. The following paragraphs assess the potential of composition bias for a number of applications by providing some evidence on $\frac{dx^u}{d\ln w^u}$.

[42] Note that I control in the paper for the cyclicality of the wage itself by subtracting the log wage of all employed in the prior year. See the notes in Table 1 in the paper for details.

The cyclicality of search intensity. Shimer (2004) and Mukoyama, Patterson and Sahin (2014) find that search intensity of unemployed workers is counter-cyclical. At the same time, Krueger and Mueller (2010) find that search intensity is highly elastic to the wage, which suggests that compositional effects among the unemployed could lead researchers to overstate the counter-cyclicality of search intensity as the pool shifts toward high-wage high-intensity searchers in recessions. Indeed Mukoyama, Patterson and Sahin (2014) find that composition effects explain about half of the observed counter-cyclicality of search effort by controlling for demographic characteristics and unemployment duration, but they do not control for the pre-displacement wage.

A simple back-of-the-envelope calculation suggests that search effort of the unemployed may increase substantially simply due to composition effects. The calculation is based on the semi-elasticity of minutes spent on job search to the log wage of around 110 (see Krueger and Mueller, 2010) and a shift towards high-wage workers in a typical recession of around 7 log points in terms of the pre-displacement wage. This yields an increase of around 8 minutes of time spent on job search per day, or around one quarter of the average daily time spent on job search, due only to composition effects. This corresponds to nearly 100 percent of the increase in time spent on job search in the last two recessions shown in Figure 3 of Mukoyama, Patterson and Sahin (2014). Of course, this is a simple back-of-the-envelope calculation, but it suggests that it may be important to control for the pre-displacement wage to fully control for compositional effects.

The cyclicality of the wage statistics related to the unemployed. Haefke, Sonntag and van Rens (2013) estimate the cyclicality of the wages of newly hired workers with data from the CPS and find that it is higher than the cyclicality of wages of job stayers. The authors adjust for potential composition bias by controlling for observable characteristics, but no information on the pre-displacement wage is used.[43] Assuming that the elasticity of the wage of newly hired workers to the pre-displacement wage is equal to 1, then compositional effects could explain an increase in the wage of newly hired workers of 7 log points in a typical recession, or 2 log points in terms of the residual wage, and thus would lead to a substantial downward bias in the pro-cyclicality of the wage of newly hired workers. As a point of comparison, Haefke, Sonntag and van Rens (2012) report that the elasticity of wages of newly hired workers to labor productivity is around 0.8, implying that wages of newly hired workers decrease by 3.2 log points in a typical recession with a 4 percent drop in labor productivity[44]. Thus, controlling for the pre-displacement wage is likely to *reinforce* the conclusion of Haefke, Sonntag and van

[43] Only a small fraction of the sample of employed are newly hired workers, and using information on pre-displacement wages would further substantially reduce the sample size.

[44] Shimer (2005) reports that the standard deviation of labor productivity is two percent for the post-war period.

Rens (2012) that wages of newly hired workers are more cyclical than wages of job stayers (in particular, because compositional shifts are shown to be an order of magnitude larger in the pool of unemployed compared to the pool of employed).[45] As argued by Haefke, Sonntag and van Rens (2012), the cyclicality of the wage of newly hired workers is a critical input for aggregate dynamics of search-matching models.

Similarly, it is important to control for the pre-displacement wage when analyzing the cyclicality of self-reported reservation wages[46], as reservation wages are strongly increasing in the pre-displacement wage with an elasticity in excess of 0.5 (see Krueger and Mueller, 2016).

Finally, the results in this paper may also explain the finding in Schmieder and von Wachter (2010) that workers with high wages due to past tight labor market conditions face higher layoff risk, as the pool of unemployed sorts towards low-wage individuals in good times. Low-wage individuals are more likely to be laid off independent of the state of the cycle (see Table 2 of this paper, which shows that separation rates for low-wage workers are twice as high) and thus individuals hired in good times may be more likely to be laid off simply due to a compositional shift towards high-layoff-risk (=low-wage) individuals in expansions.

The cyclicality of unemployment duration and job finding. Baker (1992) and more recently Krueger, Cramer and Cho (2014) and Kroft et al. (2014) find that there is no or little composition bias in the cyclicality of unemployment duration and job finding. This can easily be reconciled with the findings in this paper, as the reason for this finding is that job finding rates (and thus unemployment duration) do not differ much by wage group. In fact, Table 2 in the paper suggests that job finding rates are nearly identical for low- and high-wage workers. This suggests that even large compositional shifts towards high-wage workers in recessions have little or no impact on the aggregate job finding rate and unemployment duration.

[45] This calculation assumes that there is no selective hiring in terms of the pre-displacement wage, but the results in this paper suggest that the average as well as the cyclicality of the job finding rates is very similar across wage groups.

[46] See, e.g., Koenig, Manning and Petrongolo (2014).

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