

Unemployment Fluctuations, Match Quality, and the Wage Cyclical-ity of New Hires*

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Abstract

We revisit the issue of the high cyclical-ity of wages of new hires. We show that after controlling for composition effects likely involving procyclical upgrading of job match quality, the wages of new hires are no more cyclical than those of existing workers. The key implication is that the sluggish behavior of wages for existing workers is a better guide to the cyclical-ity of the marginal cost of labor than is the high measured cyclical-ity of new hires wages unadjusted for composition effects. Key to our identification is distinguishing between new hires from unemployment versus those who are job changers. We argue that to a reasonable approximation, the wages of the former provide a composition-free estimate of the wage flexibility, while the same is not true for the latter. We then develop a quantitative general equilibrium model with sticky wages via staggered contracting, on-the-job search, and heterogeneous match quality, and show that it can account for both the panel data evidence and aggregate evidence on labor market volatility.

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1 Introduction

Aggregate wage data suggests relatively little variation in real wages as compared to output and unemployment. This consideration has motivated incorporating some form of wage rigidity in quantitative macroeconomic models to help account for business cycle fluctuations, an approach that traces back to the early large scale macroeconometric models and remains prevalent in the recent small scale DSGE models.¹ Such considerations have also motivated the inclusion of wage rigidity in search and matching models of the labor market in the tradition of Diamond, Mortensen and Pissarides. Most notably, Shimer (2005) and Hall (2005) show that the incorporation of wage rigidity greatly improves the ability of search and matching models to account for unemployment fluctuations.²

An influential paper by Pissarides (2009), however, argues that the aggregate data may not provide the relevant measure of wage stickiness: What matters for employment adjustment is the present discounted value of wages of new hires, which needs to be disentangled from aggregate measures of wages. In this regard, there is a volume of panel data evidence beginning with Bils (1985) that finds that entry wages of new hires are substantially more cyclical than the wages of existing workers. Further, it is then possible to account for the inertia in existing workers wages by appealing to wage smoothing that stems from an implicit contracting arrangement (e.g., Beaudry and DiNardo, 1991). Pissarides then interprets the findings in this literature as evidence for a high degree of contractual wage flexibility among new hires, which in turn implies a high degree of flexibility in the marginal cost of labor. The net effect is to call into question efforts to incorporate wage rigidity into macroeconomic models.

In this paper, we revisit new hire wage cyclicalities and the associated implications for aggregate unemployment fluctuations. We argue that the interpretation of new hire *wage cyclicalities* as direct evidence of *wage flexibility* ignores confounding cyclical variation in wages that is due to workers moving to better job matches during expansions. As we make clear, failing to control for this composition effect on wage changes leads to significant upward bias in the measure of the procyclicality of the marginal cost of labor. We then adopt a novel empirical strategy to separate contractual wage flexibility from cyclical match quality. We find that after controlling for composition effects, the wages of new hires are no more flexible than those of existing workers. A key implication, which we make precise, is that the low variability of existing workers' wages provides a better guide to the cyclicalities

¹ See for, example, Christiano, Eichenbaum and Evans (2005), Smets and Wouters (2007), Gertler, Sala and Trigari (2008), Galí, Smets and Wouters (2011), Christiano, Eichenbaum and Trabandt (2015), and Christiano, Eichenbaum and Trabandt (2016).

² Gertler and Trigari (2009), Hall and Milgrom (2008), Blanchard and Galí (2010), and Christiano, Eichenbaum and Trabandt (2016) build on this approach and model the wage setting mechanism in greater detail.

of the marginal cost of labor than does the high volatility of new hire wages (unadjusted for composition). We then develop a quantitative macroeconomic model that is able to account for both the aggregate and panel data evidence.

Key to our identification of composition effects is the distinction between new hires who are job changers versus those coming from unemployment. We argue based on both theory and evidence that procyclical upgrading of job match quality is predominant among job changers. The main reason that a worker with a job moves is to improve the match and the opportunity for these workers to upgrade is procyclical. Thus, by failing to control for wage changes reflecting changes in match quality, estimates of the wage cyclicalities of job changers overstate true wage flexibility. By contrast, under a standard assumption in the literature about the quality distribution of available jobs, upgrading of match quality is acyclical for workers coming from unemployment. In our view, further, the baseline assumption of no cyclical upgrading for these types of workers is consistent with a reasonable reading of the evidence. Given this assumption, accordingly, the wage cyclicalities of new hires from unemployment provides a reasonable composition-free estimate of new hire wage flexibility.

To develop our estimate of new hire wage flexibility, we construct a unique data set from the Survey of Income and Program Participation (SIPP) that allows us to separately estimate the wage cyclicalities of new hires from unemployment versus that of those making job-to-job transitions. We first show that by pooling the two types of new hires with our data, we can replicate the typical result of the existing literature: New hire wages appear to be more flexible than the wages of continuing workers. When we estimate separate terms for both types of new hires, however, we find no evidence of excess wage cyclicalities for new hires coming from unemployment, but substantial evidence of this phenomenon for workers making job-to-job transitions. We then discuss how our estimates suggest considerable sluggishness in the marginal cost of labor, consistent with the macroeconomic models that feature wage rigidity described above.

Even if one does not accept our identifying assumptions, our panel data estimates provide a new set of conditional moments that any macroeconomics model of unemployment fluctuations must confront. To illustrate, we develop a search and matching model with the following three modifications (*i*) staggered wage contracting, (*ii*) variable match quality, and (*iii*) on-the-job search with endogenous search intensity. We show that the model is consistent with both the aggregate data and the panel data evidence on the relative cyclicalities of the wages of new hires from unemployment versus job changers. In particular, while the wages of new hires are sticky within the model, cyclical improvements in match quality for job changers generate new hire wage cyclicalities, offering the appearance of wage flexibility among new hires. All the three modifications of the model are critical for reconciling the aggregate and panel evidence.

Our results are consistent with a rich literature on earnings growth and job-to-job transitions. Beginning with Topel and Ward (1992), an extensive empirical literature has documented that a large fraction of the wage increases experienced by a given worker occur through job-to-job transitions. Such job movements can be understood as employed workers actively searching for higher paying jobs, along the lines of Burdett and Mortensen (1998). A related theoretical literature has shown that such match improvements are more easily realized during expansions than during recessions (Barlevy, 2002; Menzio and Shi, 2011). In contrast, such job-ladder models offer no systematic prediction for wage changes of workers searching from unemployment, as such workers are predicted to adopt a reservation wage strategy that is not contingent on their most recent wage. Beyond this theoretical prediction, as we will show, there is evidence to suggest that our baseline assumption that composition effects are relevant for job changers but not for new hires from unemployment is a reasonable approximation of reality.

This paper is also related to Gertler and Trigari (GT, 2009), which controls for composition effects on new hire wage cyclicalities allowing for a job-person fixed effect on wages. The advantage of the current approach is that the wage cyclicalities of new hires from unemployment provides a directly observable composition free measure of new hire wage flexibility.³ By distinguishing between new hires from unemployment versus job changers, further, we obtain a new set of facts that macroeconomic models of unemployment and wage dynamics must confront. We then develop such a model.

Other work with a message similar to this paper includes Hagedorn and Manovskii (2013). These authors make clever use of an indirect measure of match quality – specifically, the sum of log market tightness over different durations of a worker’s employment – to show that findings that have been previously interpreted as evidence of implicit contracts can be accounted for by composition effects. In addition to using a more direct way to control for composition effects, we differ by analyzing how estimates of excess new hire wage cyclicalities can be reconciled with models of wage stickiness used to account for aggregate labor market dynamics. Also relevant are papers that use Portuguese data, including Martins, Solon and Thomas (2012) and Carneiro, Guimaraes and Portugal (2013), and German data, including Stüber (2017). Using different methods, the estimates in these papers also suggest that new hire wage cyclicalities are roughly the same as that for continuing workers.⁴

In terms of empirical methodology, our paper is closest to Haefke, Sonntag and van Rens (2013) who examine directly the wage cyclicalities of new hires from unemployment.

³ Gertler and Trigari (2009) also requires an additional identifying assumption: There must be recontracting of wages at some point over the worker’s observed history with the firm. Otherwise, it is not possible to distinguish the firm/worker fixed effect from an implicit contract where the wage is permanently indexed to aggregate conditions in the first period of a match.

⁴ However, overall real wage variation in these data exhibits greater procyclicality than in the U.S., suggesting some limits to the relevance of this evidence to U.S. labor market volatility.

They use cross-sectional data from the CPS and recover point estimates suggestive of excess wage cyclicality of new hires from unemployment, although not statistically significant. We instead use a rich, high-frequency panel data set from the SIPP. The panel aspect of our data permits sharp controls for unobserved heterogeneity and compositional effects. To this end, we find statistically significant evidence that new hires wages from unemployment are no more cyclical than for existing workers. As a corollary, we show that the excess wage cyclicality of new hires recovered by the literature is entirely driven by new hires from employment, raising the possibility that this excess cyclicality is an artifact of cyclical movements in match quality via the job ladder, as opposed to true wage flexibility. Finally, as noted earlier, we develop a macroeconomic model of labor market dynamics and show that simulated data from the model is consistent with both the aggregate and panel data evidence.

Section 2 provides the new panel data evidence. We first describe the data and the econometric methodology we use to identify a composition-free estimate of the marginal cost of labor. We then present evidence that new hire wages are no more flexible than those of existing workers, as well as a variety of robustness exercises that support this finding. Section 3 describes the model and Section 4 shows how the model generates composition bias. Section 5 presents the numerical results and also demonstrates how the model can reconcile the aggregate and panel evidence. Section 6 then discusses the implications for the cyclicality of the marginal cost of labor, including the relevance of our results for Kudlyak’s (2014) notion of the “user cost of labor”. Concluding remarks are in Section 7.

2 Data and Empirics

In this section we present evidence on the relative cyclicality of new hires’ wages using a rich data set. We first describe the data. We next revisit the results on excess cyclicality of new hire wages. We then present new evidence based on making the distinction between new hires from employment (i.e., job changers) versus new hires from unemployment. In doing so, we use a data generating model to make concrete the assumptions we use to identify a composition-free estimate of new hire wage flexibility. We conclude the section with some evidence on the robustness of our identifying assumptions.

2.1 Data

We use data from the Survey of Income and Program Participation (SIPP) from 1990 to 2012. The SIPP is administered by the U.S. Census Bureau and is designed to track a nationally representative sample of U.S. households. The SIPP is organized by panel years, where each panel year introduces a new sample of households. Over our sample period the

Census Bureau introduced eight panels. The starting years were 1990-1993, 1996, 2001, 2004, and 2008. The average length of time an individual stays in a sample ranges from 32 months in the early samples to 48 months in the 2008 panel.

Most key features of the SIPP are consistent across panels. Each household within a panel is interviewed every four months, a period referred to as a wave. During the first wave that a household is in the sample, the household provides retrospective information about employment history and other background information for working age individuals in the household. At the end of every wave, the household provides detailed information about activities over the time elapsed since the previous interviews, including job transitions that have occurred within the wave. Although individuals report earnings for each month of the wave, we only use reported earnings from the last month of the wave to accommodate the SIPP “seam effect.”⁵

The SIPP has several features that make it uniquely suited for our analysis. Relative to other commonly used panel data sets, the SIPP follows many more households, follows multiple representative cohorts, and is assembled from information collected at a high frequency (e.g. surveys are every four months as opposed to annually). This high frequency structure of the data is crucial for constructing precise measurements of employment status and wages. In particular, we use job-specific earnings to generate monthly records of job-holding for each individual, allowing us to discern direct job-to-job transitions from job transitions with an intervening spell of non-employment.⁶ As the SIPP contains multiple cohorts, at each point in time the sample is always representative of the U.S. population, in contrast to other widely used panel data sets such as the NLSY.

Crucial to our approach is that the SIPP maintains consistent job IDs. Fujita and Moscarini (2017) document that, starting with the 1996 SIPP wave, a single job may be assigned multiple IDs for an identifiable subset of survey respondents. In the appendix, we develop a procedure that exploits a feature of the SIPP employment interview module that allows us to identify jobs that may have been assigned multiple IDs. We find evidence for recall employment, corroborating Fujita and Moscarini (2017)’s finding that recalls compose a significant fraction of transitions to employment from non-employment.⁷

⁵ Specifically, we find that the vast majority of earnings changes for workers continuously employed at the same job across multiple waves occur between waves, as opposed to during a wave. The “seam effect” is discussed in greater detail in the SIPP User’s Guide (U.S. Census Bureau, 2001, 1-6).

⁶ Starting with the 1996 panel, respondents report the start and end dates associated with a job. While our measure is highly correlated with the self-reported measure, the self-reported measure is sometimes inconsistent with self-reported activity from other waves— e.g., a worker will report a starting date that corresponds to a prior wave for which the respondent had previously reported being unemployed or employed at a different job. We use our earnings-based measure for all panels to avoid such issues of measurement error and maintain consistency in our analysis of the pre- and post-1996 data.

⁷ We do not include these observations as new hires in our analysis; if these workers receive wages that are only as cyclical as “stayers”, they would bias the estimation of wage cyclicity of new hires from unemployment downwards.

The appendix provides further discussion of the data and the construction of the variables we use in the estimation.

2.2 Baseline Empirical Framework

Before turning to our econometric framework, we first replicate the evidence in the literature that new hire wages are more cyclical than those of existing workers. To do so we employ a simple statistical framework to study the response of individual level wages to changes in aggregate conditions that has been popular in the literature, beginning with Bils (1985).⁸ We regress the log wage of individual i at time t , w_{it} , on individual level characteristics x_{it} , including education, job tenure, and a time trend; the unemployment rate u_t ; an indicator variable $\mathbb{I}\{N_{it} = 1\}$ equal to one if the worker is a new hire and zero if not; and an interaction term $\mathbb{I}\{N_{it} = 1\} \cdot u_t$. To control for unobserved characteristics, we estimate a regression equation in first differences and fixed effects. Our measurement equation estimated in first differences reads:

$$\Delta \log w_{it} = \Delta x'_{it} \pi_x + \pi_u \cdot \Delta u_t + \mathbb{I}\{N_{it} = 1\} \cdot [\pi_n + \pi_{nu} \cdot \Delta u_t] + e_{it} \quad (1)$$

where Δ denotes first-differences and e_{it} is random error term.⁹ The analog equation estimated in fixed effects is obtained by replacing Δ with Δ^m in (1), with Δ^m denoting mean-differences.

The inclusion of the unemployment rate in the regression is meant to capture the influence of cyclical factors on wages, while the interaction of the new hire dummy with the unemployment rate is meant to measure the extra cyclicity of new hires wages. In particular, the coefficient π_u can be interpreted as the semi-elasticity of wages with respect to unemployment, while $\pi_u + \pi_{nu}$ gives the corresponding semi-elasticity for new hires.¹⁰

The regressions are based on triannual data, i.e. data at a four month frequency.¹¹

⁸ Included among the many studies regressing individual level wages on some measure of unemployment as a cyclical indicator are Beaudry and DiNardo (1991); Shin (1994); Solon, Barsky, and Parker (1994); Barlevy (2001); Carneiro, Guimarães, and Portugal (2012); Devereaux (2002); Martins, Solon, and Thomas (2012); and Hagedorn and Manovskii (2013).

⁹Note, our notation is “compact”, in the sense that it does not directly acknowledge that differenced wage observations might span several jobs, or that the time between wage observations might vary for new hires with a non-employment spell (i.e., we could have $\Delta \log w_{it} = \log w_{it} - \log w_{i\tau}$, where $\tau < t - 1$).

¹⁰The empirical definition of the cycle is implicit in the regression specification. In the FE estimation, the cycle is defined by deviations of the unemployment rate from its three/four-year average over the panel. In the FD specification, it corresponds to the four-month change in the unemployment rate. Given the high volatility and fast transition dynamics of unemployment, the FD specification preserves the underlying relation without removing meaningful cyclical variation.

¹¹ While we have monthly information on earnings and job mobility, the data are collected once every four months and there is reasonable suspicion of correlated measurement error of reported earnings within waves. We follow Gottschalk (2005) in limiting our analysis to reports of earnings from the final month of each four month wave.

For comparability to Bils (1985), we only use observations for men between the ages of 20 and 60. Accordingly, unemployment is the prime age male unemployment rate. We use job-specific earnings to construct our measure of wages. In cases in which an hourly wage is directly available, we use that as our measure. In cases in which an hourly wage is not directly available, we use job-specific earnings divided by the product of job-specific hours per week and job-specific weeks per month. Wages are deflated by the monthly PCE. Finally, we define “new hires” as individuals who are in the first four months of their tenure on a job.¹² The appendix provides additional information on variable construction, including the individual level characteristics we use. Finally, we compute robust standard errors, clustered at the individual level.

Table 1 presents the results. They are consistent with the key findings of the literature: π_{nu} is statistically significant and negative (along with π_u), suggesting greater cyclical sensitivity of new hires’ wages. The first column presents the estimates of equation (1) using first differences and the second presents estimates using fixed effects. The results are robust across specifications. Similar to Bils (1985), we find that new hires’ wages are significantly more cyclical than those for existing workers. When estimating the equation in first differences, the semi-elasticity of new hire wages is -1.595 , compared to -0.461 for continuing workers. With fixed effects, the new hire semi-elasticity is estimated to be -1.789 , compared to -0.147 for continuing workers.

While we recover precise coefficient estimates of the relative wage cyclicity of new hires versus continuing workers that are consistent with earlier literature, our estimates of absolute wage cyclicity are smaller. Using annual NLSY data from 1966-1980, Bils (1985) finds a continuing worker semi-elasticity of 0.6, versus 3.0 for changers. Barlevy (2001) uses annual data from the PSID and NLSY through 1993 and recovers semi-elasticities of 2.6 and 3.0 for job changers. The differences between our estimates of wage cyclicity and those from of this earlier literature are not due to the higher frequency of our data: When we re-estimate our model using data at the annual frequency we find very similar results to our baseline triannual frequency. Another possible source of the discrepancy is the difference in sample period. Our SIPP data only goes back to 1990, which means our sample is much later than that used in the earlier work. In any case, our quantitative model will generate data consistent with the degree of wage cyclicity suggested by the evidence in Table 1.

2.3 Reconsidering the New Hire Effect

As we noted earlier, a popular interpretation of the results in Table 1 is that they are indicative of contractual wage flexibility for new hires, e.g. Pissarides (2009). According

¹² Note that given this definition we will only have one wage observation for a new hire since we only use the final month of a four-month wave to obtain wage data.

to this view, the present value of wages is highly responsive to the aggregate state, but the path of wages is smoothed over the lifetime of the wage contract. Hence, the negative and significant estimate for π_{nu} reflects that new hires receive a contract with persistently higher wages when hired during a boom. In turn, the smaller estimate for π_u reflects that wages are insulated from aggregate conditions for the rest of the match.

We offer an alternative interpretation: Rather than indicating excess wage flexibility, the estimated new hire wage cyclicalities might instead be due to “cyclical composition effects”, whereby workers in existing jobs move to better jobs at a higher rate during expansions, and a slower rate during contractions. Under this scenario, the estimated high cyclicalities of new hire wages from the Bils’ equation will not reflect true excess wage flexibility.

Figure 1 illustrates how procyclical match upgrading may bias estimates of new hire wage cyclicalities. The figure portrays cyclical wage variation across two jobs: a good match and a bad match. The wage in each match (solid line) is modestly cyclical around a steady state wage (dotted line). Consider, however, an expansion that facilitates the movement of workers in bad matches to good matches. There are two cyclical components of such a worker’s wage increase: (i) a modest cyclical increase in wages common to both job changers and continuing workers and (ii) the improvement in match quality. Note, from the perspective of a firm, the wages of job changers and continuing workers are equally flexible; that is, the cyclical wage increase of job-changers does not translate to a cyclical increase in the marginal cost of labor to the firm. However, an econometrician who does not take into account the cyclical change in match quality may conclude otherwise.

To test for excess wage flexibility of new hires relative to existing workers, we make the distinction between new hires coming from other jobs versus those coming from unemployment. We first argue that cyclical selection bias works mainly through job-changers who are more likely to upgrade their match quality in booms than in recessions. This conceptual framework is consistent with (i) an empirical literature finding that job changers realize substantial wage gains from switching jobs (Topel and Ward, 1992), and (ii) a theoretical literature arguing that workers in employment are more likely to select into better matches during expansions than recessions (Barlevy, 2002).

Second, we assume that for workers coming from unemployment, there is no selection bias. Our argument is reasonable to the extent that the quality distribution of jobs available to a given individual is largely invariant to the aggregate state.¹³ In Section 2.4, we discuss the robustness of this assumption. Given this identifying restriction, the wage cyclicalities of new hires from non-employment serves as a valid measure of the cyclicalities of the composition-adjusted hiring wage.

¹³ While this is a strong assumption, it is similar to Hagedorn and Manovskii (2013), whose baseline model features a wage offer distribution that is invariant to the business cycle; and considerably weaker than Kudlyak (2014), who assumes no cyclical composition in new hire wages.

To formalize our identification strategy, we consider a simple data-generating model (DGM) that can approximate the full equilibrium model that we develop later in Section 3 (as we show in Section 4). Under the approximate DGM,

$$\log w_{it} = \psi_0 + x'_{it}\psi_x + \psi_u \cdot u_t + \alpha_i + \alpha_{it} + \varepsilon_{it}, \quad (2)$$

where ψ_u gives the common wage semi-elasticity for new and continuing workers, α_i is a time-invariant person fixed effect, α_{it} is unobserved match quality for individual i at a given job at time t , and ε_{it} is an *iid* error term.

We next consider a process for average match quality $\bar{\alpha}_{it}$. In particular, we suppose that match quality evolves as follows:

$$\Delta \bar{\alpha}_{it} = \mathbb{I}\{EE_{it} = 1\} \cdot [\psi_n^{EE} + \psi_{nu}^{EE} \cdot \Delta u_t] + \mathbb{I}\{ENE_{it} = 1\} \cdot \psi_n^{ENE}, \quad (3)$$

where $\mathbb{I}\{EE_{it} = 1\}$ is an indicator equal to one if the worker is a new hire who makes a direct employment to employment transition and zero otherwise; and where $\mathbb{I}\{ENE_{it} = 1\}$ equals one if the worker is a new hire with an intervening spell of unemployment and zero otherwise. Equation (3) describes a process for average match quality in which workers in continuing matches experience no change in match quality, workers hired from non-employment incur a level change in match quality independent of the cycle, and job changers incur a change in match quality that also depends on the change in unemployment. As the unemployment rate falls, job-changers are more likely to move to higher-paying matches, and vice versa when the rate rises. Hence, the change in average match quality for job-changers is proportional to the change in the unemployment rate.¹⁴ Workers coming from unemployment, by contrast, have acyclical changes in match quality, as they are more likely to take the first job they find regardless the state of the cycle.

To see how the typical regression of the literature may yield misleading evidence of new hire wage flexibility, we first take first differences of the DGM (2), integrate over changes

¹⁴For the full model, Section 4 shows something similar: the change in average match quality from time $t - 1$ to time t is proportional to the change in the distribution of workers across different match qualities. The change in average match quality across periods itself depends in part on the change in unemployment.

in unobserved match quality $\Delta\alpha_{it}$ over new hires, and then combine with (3)^{15,16}:

$$\begin{aligned}\Delta \log w_{it} &= \Delta x'_{it}\psi_x + \psi_u \cdot \Delta u_t \\ &+ \mathbb{I}\{EE_{it} = 1\} \cdot [\psi_n^{EE} + \psi_{nu}^{EE} \cdot \Delta u_t] \\ &+ \mathbb{I}\{ENE_{it} = 1\} \cdot \psi_n^{ENE} + \Delta\epsilon_{it}.\end{aligned}\tag{4}$$

As can be seen from comparing equations (1) and (4), the Bils regression is misspecified under our DGM. In particular, it imposes that the wage semi-elasticities of job changers and new hires from unemployment are equal and given by π_{nu} . By contrast, our DGM implies that the elasticity for job changers is $\psi_{nu}^{EE} < 0$ and the elasticity for new hires from unemployment is zero. Accordingly, taking the Bils equation to the data will lead to an estimate $\hat{\pi}_{nu} < 0$, but this will be due to the composition bias captured by ψ_{nu}^{EE} . Indeed, as we show in the appendix, $\hat{\pi}_{nu} \propto \psi_{nu}^{EE}$. Thus, under our DGM, the estimates of excess new hire wage cyclicalities reflect composition bias rather than true flexibility.

We can test whether the data is consistent with the simple DGM by estimating a version of equation (1) that includes separate interaction terms for job changers versus new hires from unemployment.¹⁷

$$\begin{aligned}\Delta \log w_{it} &= \Delta x'_{it}\pi_x + \pi_u \cdot \Delta u_t \\ &+ \mathbb{I}\{EE_{it} = 1\} \cdot [\pi_n^{EE} + \pi_{nu}^{EE} \cdot \Delta u_t] \\ &+ \mathbb{I}\{ENE_{it} = 1\} \cdot [\pi_n^{ENE} + \pi_{nu}^{ENE} \cdot \Delta u_t] + e_{it},\end{aligned}\tag{5}$$

Under the null of our DGM,

$$\begin{aligned}\pi_{nu}^{EE} &= \psi_{nu}^{EE} \\ \pi_{nu}^{ENE} &= 0\end{aligned}$$

implying that (i) the excess wage cyclicalities for job changers reflects composition bias and

¹⁵ Section A.6 in the appendix shows how procyclical changes in composition of workers making job-to-job changes (as in the full equilibrium model) map into procyclical changes in average match quality (as in the approximate DGM) once we integrate over changes in unobserved match quality $\Delta\alpha_{it}$ over new hires. Thus, the approximate DGM is consistent with the primary mechanism of the full model.

¹⁶ Our results are robust to using as the cyclical indicator a distributed lag of current and past unemployment rates, as would be implied by the kind of staggered wage contracting model we develop later in the paper. See section A.5 of the online appendix to this paper.

¹⁷ We differ from Haefke *et al.* (2013) in two key dimensions. First, we estimate our equations in fixed-effects and first-differences to control for unobserved heterogeneity in workers; Haefke *et al.* (2013) use cross-sectional data from the CPS. Second, we follow the majority of the literature in using the unemployment rate as a cyclical indicator, whereas Haefke *et al.* use labor productivity. Unemployment is a valid cyclical indicator across a variety of business cycle episodes, whereas the relation between labor productivity and the cycle has proved to be less stable over time.

(ii) there is no excess wage cyclicality for new hires from unemployment. As we show, our estimates are all consistent with the null of $\pi_{nu}^{ENE} = 0$.

The fixed-effects estimator shares the same crucial properties: namely, π_u and π_{nu}^{ENE} are consistent estimators for ψ_u and ψ_{nu}^{ENE} , so that we obtain composition-free estimates of the excess wage flexibility of new hires. We confirm that the fixed-effects estimator yields estimates consistent with the null that $\pi_{nu}^{ENE} = 0$.¹⁸

Table 2 presents the results just mentioned, in first differences and fixed-effects. For robustness, we consider two different measures of what constitutes a new hire from non-employment. In our most narrow measure, an individual is classified as a job-changer only if the individual is recorded at a new job with no interruption in earnings. In the second measure, we also classify new hires with a single month of no earnings between jobs as job-changers, allowing for the possibility that the worker found the new job from employment but took a short break between job spells.

Across all specifications, we never recover a significant new hire effect for new hires from non-employment: the coefficient estimates for π_{nu}^{ENE} are small in magnitude and not statistically different from zero. Thus, for new hires from unemployment, wages are no more cyclical than those for existing workers. Meanwhile, we find substantial evidence of procyclical changes in match quality for job changers.¹⁹ Indeed, the coefficient π_{nu}^{EE} on the job-changer interaction term is higher than the coefficient π_{nu} on the interaction term for the baseline regressions in Table 1, where both types of new hires are pooled together. In every case, we can reject the null hypothesis that the wage cyclicality for new hires from non-employment equals the wage cyclicality for new hires from employment at the 5% level.

2.4 Robustness

We interpret the lack of statistical significance of the interaction term for new hires from unemployment as evidence against new hire wage flexibility. However, an alternative inter-

¹⁸ As we show in the appendix, fixed-effects and first-differences imply different limiting distributions for π_{nu}^{EE} under the approximate DGM, so our estimates for ψ_{nu}^{EE} in fixed effects will generally be biased. Once we turn to the full model, however, we are able to match the separate wage semi-elasticities in first differences and fixed effects.

¹⁹ A recent working paper by Hahn, Hyatt, and Janicki (2018) uses quarterly data on earnings from the LEHD for eleven states from 1996 to 2015. They find that the wage cyclicality of job-changers and new hires from non-employment are very similar. However, for three reasons, we suspect that their estimates are likely to be imprecise relative to ours: (1) they use an imputed measure of wages, whereas we work with a direct measure; (2) given that we have monthly data, we can draw a sharper distinction between job-changers and new hires from unemployment than they can from their quarterly data; (3) we have a more representative and longer sample; and (4) they are unable to control for occupation, which we show in Section 2.4 can be important for eliminating a spurious new hire effect. Another working paper by Bauer and Lochner (2017) uses German administrative data provided by the Institute for Employment Research (IAB), from 2000 to 2014. They also confirm, among other things, that it is important to control for occupational mobility within a Bils' type regression that distinguishes between new hires from unemployment and job changers.

pretation of our results is that new hires from unemployment are subject to a *countercyclical* composition bias that by coincidence exactly offsets wage cyclical due to new hire wage flexibility. Under such a scenario, we could fail to reject the null hypothesis that $\pi_{nu}^{ENE} = 0$ when new hires wages are indeed flexible.

In this section, we explore such a possibility by considering an expanded set of regressions similar to (5), but where we control for various forms of composition bias that have been emphasized in the existing literature. In doing so, we are able to isolate subsets of *ENE* transitions that are less likely to be contaminated by a cyclical composition bias. Hence, if our previous estimates were confounded by countercyclical composition for *ENE* workers, we should be more likely to recover a new hire effect consistent with flexible wages in these more restricted samples of *ENE* workers. However, the results continue to consistent with the hypothesis that the wages of newly hired workers are no more flexible than of continuing workers.

First, we consider *EE* and *ENE* new hires who switch or remain in the same occupation or industry when moving into a new job. Indeed, the literature has emphasized inter-occupation and industry mobility as a natural candidate by which workers may “cyclically upgrade” into higher-paying jobs during an expansion, e.g. Vroman (1977). Much of the literature has emphasized the importance of cyclical upgrading both across industries and occupations, although we note that there has been little in the way of empirical work to explore separate implications for employed and unemployed workers. McLaughlin and Bils (2001) document a set of industry employment and wage patterns consistent with cyclical upgrading and show that a model of selection of workers into industries by comparative advantage can explain these patterns. Chodorow-Reich and Wieland (2018) use a model with industry-switching among employed and unemployed workers to explore the interaction of sectoral reallocation and business cycle conditions. Kambourov and Manovskii (2009) argue that occupational tenure is more important than industry or employer tenure in explaining variation in wages, suggesting that cyclical patterns in occupation switching should also be important for explaining cyclical variation in wages. Indeed, Altonji, Kahn, and Speer (2016) argue that initial occupational placement is important for explaining cross-section variation in the cost of entering the labor market during a recession (Kahn, 2010). Huckfeldt (2016) documents that occupation-downgrading is countercyclical among displaced workers, helping to account for the cyclical cost of job loss (Davis and von Wachter, 2011).²⁰

²⁰ Taken together, the existing evidence on displaced workers and new entrants suggests that if anything, there should be a *procyclical* composition bias associated to occupation switching among *ENE* workers. However, displaced workers are a subset of the non-employed, and the focus on wage growth precludes us to considering new entrants to the labor market. Thus, *a priori*, it is not clear whether the bias for *ENE* would also be procyclical.

Table 3 gives the results for *EE* and *ENE* new hires where we control for a cyclical composition effect that may be due to occupation or industry switching. The semi-elasticities for *EE* and *ENE* occupation/industry non-switchers are given in rows two and three; rows four and five give the differential cyclicality for switchers. As emphasized above, we consider the semi-elasticity for *ENE* non-switchers to be the relevant measure of new hire wage cyclicalities, as it is least likely to be contaminated by a composition bias. Moreover, to the extent that similar jobs are indeed grouped by industry or occupation, we are better able to isolate true wage cyclicalities by focusing on workers who remain in the same type of job across an employment transition. As before, we interpret the *EE* elasticities to represent the role of cyclical self-selection of workers searching on-the-job; our estimates here allow us to evaluate whether procyclical selection into better jobs is concentrated among *EE* switchers or non-switchers.

From our estimates in fixed effects, we find evidence that *ENE* occupation/industry switchers have more cyclical wages than *ENE* stayers, suggesting that the composition bias introduced by occupation/industry switching is procyclical rather than countercyclical. Among *EE* workers, we find evidence of a stronger procyclical composition effect for non-switchers than switchers, but both are estimated to be procyclical.²¹ For both first-differences and fixed-effects, however, our findings on *ENE* wage cyclicalities are largely unchanged: we recover point-estimates for π_{nu}^{ENE} that are positive, not significant, and for the most part, close to zero.

Next, we consider composition effects due to unobserved characteristics that are correlated with unemployment duration. While unemployment duration has been identified as crucial for understanding re-employment wage outcomes (see Schmieder, von Wachter, and Bender, 2015), there are multiple reasons why unemployment duration might matter for wages, and the overall cyclicalities of the associated composition bias is ambiguous. For example, Ljungqvist and Sargent (1998) argue that workers who experience longer durations of unemployment are subject to greater human capital loss, and hence lower re-employment wages. Therefore, longer unemployment durations during a recession could introduce a procyclical bias. The literature has also identified stigma effects associated to the duration of the unemployment spell.²² This could generate a countercyclical composition bias à la Mortensen and Pissarides (1994): if workers with long unemployment spells must be of

²¹ We speculate the presence of important asymmetries between switchers and non-switchers among the employed and unemployed. For example, if within-industry or within-occupation hiring standards are countercyclical (as documented for occupation by Hershbein and Kahn, 2018), an unemployed worker during a recession might be unable to find a job in his previous occupation or industry and be forced to search for a job in a worse one. This is a procyclical composition effect that would be absent for job-changers, perhaps accounting for sign differences in the “switcher” coefficient for *EE* and *ENE* workers.

²² For example, Kroft, Lange, and Notowidigdo (2013) find that workers of longer unemployment durations are less likely to be called for an interview relative to a worker with a shorter duration of unemployment who is otherwise identical.

higher ex-post match quality to compensate for stigma effects, the average long-duration worker hired during a recession should be of higher quality than during an expansion; in contrast workers with short unemployment durations are less likely to be affected by countercyclical hiring standards.²³

Tables 4 and 5 contain results for *EE* and *ENE* new hires where we control for duration of non-employment, by first differences and fixed-effects. We estimate separate wage semi-elasticities for new hires from non-employment with non-employment durations less than or equal to τ months and new hires from non-employment with durations greater than τ months, with the two groups identified by the indicator variables *ENE* and *LTU*. For analogous reasons as before, we consider the *ENE* coefficient as the primary coefficient of interest. We estimate separate regressions for $\tau = 9, 8, 7, 6$, and 5. For each value of τ , we estimate the regression equation without controlling for occupation or industry switchers, and controlling for occupation switchers. In Tables B.2 and B.3 of the appendix, we estimate the same regressions, but controlling for industry switchers.

Once again, our results are unchanged. When we isolate shorter duration workers without controlling for occupation or industry switching, the *ENE* coefficient is negative and larger in magnitude, but never statistically significant. Additionally, once we control for occupation and industry switching, the coefficient estimates for *ENE* tend to switch signs and become positive. In the first-differences estimation, the differential effect for short-duration *ENE* occupation or industry switchers is negative (consistent with a procyclical composition effect) but not statistically different from zero. In our fixed-effects estimation, however, these coefficients become statistically significant.²⁴ Our estimates suggest that controls for occupation and industry may be important when estimating true *ENE* wage cyclicity across different groups of workers.

Overall, our estimates from this section are consistent with those from our baseline regressions: That is, even after controlling for composition bias of *ENE* workers based on observables, we find no evidence of new hire wage flexibility. While these exercises may not definitely rule out composition bias for these types of workers, our results in this section suggest that this possibility is less likely. At a minimum, further, our results provide a set of conditional moments that any model of unemployment and wage dynamics must satisfy. That is, within such a model, only the wages of job changers should exhibit excess cyclicity. New hire wages from unemployment should be no more cyclical than those of existing workers.

²³ To be clear, Mortensen and Pissarides (1994) abstracts from endogenous hiring standards by assuming that all matches are created with the highest match productivity. This assumption can be relaxed, as in Barlevy (2002).

²⁴ As we discuss in the appendix in the context of the approximate DGM, the fixed-effects and first-differences estimators do not generally yield identical coefficient estimates.

Finally, note that our approach of isolating subsets of *ENE* workers who are unlikely to have been effected by composition bias implicitly requires that cyclical composition be related to observable characteristics of the worker prior to the match. Suppose instead that the relevant composition bias for *ENE* workers arises from selection on ex-post match characteristics à la Mortensen and Pissarides (1994), but without respect to ex-ante characteristics of the worker. Under such a scenario, where the bias is presumed to be uniform, we would be unable to find a subgroup of *ENE* workers unaffected by the bias. However, a literature evaluating the quantitative importance of selection on the basis of ex-post characteristics suggests that it must play only a minor quantitative role for generating cyclical bias in the average wage growth of new hires from unemployment. In particular, a countercyclical bias in estimates of new hire wage cyclicalities could emerge if workers hired from unemployment during a recession are systematically hired into better matches, so that wage declines for new hires from unemployment will be understated during a recession. But Barlevy (2002) evaluates exactly such a scenario within an MP model and finds it to have little quantitative power in explaining cyclical changes in match quality. On the other hand, if better matches are destroyed during recessions, so that workers hired from unemployment come from higher wage matches, this type of selection has the potential to overstate the true extent of wage declines during contractions. Not only this second mechanism makes the overall cyclical impact of selection on the basis of ex-post match characteristics theoretically ambiguous, but Mueller (2017) shows that a plausibly calibrated MP model with endogenous job destruction can only generate compositional shifts that are tiny in magnitude.²⁵ Hence, we view composition bias arising from selection on ex-post match characteristics to be of negligible quantitative importance.

Even if one does not accept our evidence about composition effects, our panel data evidence provides a new set of conditional moments that can be used to discipline macroeconomic models of unemployment fluctuations. In the next section, accordingly, we develop a model that can account for not only the aggregate evidence but also our cross-sectional evidence of the relative cyclicalities of job changers wages versus those of new hires from unemployment.

3 Model

We model employment fluctuations using a variant of the Diamond, Mortensen, and Pissarides search and matching framework. Our starting point is a simple real business cycle

²⁵ Mueller then argues that a plausible explanation for the composition shifts in the pool of unemployed workers that he documents in the data is heterogeneity in ex-ante individual characteristics. We control for such individual characteristics through our use of panel data methods, as in Solon, Barsky, and Parker (1994).

model with search and matching in the labor market, similar to Merz (1995) and Andolfatto (1996).

We make two main changes to the Merz/Andolfatto framework. First we allow for staggered wage contracting with wage contracts determined by Nash bargaining, as in GT (2009). Second, we allow for both variable match quality and on-the-job search with variable search intensity. These features will generate procyclical job ladder effects, in the spirit of Barlevy (2002) and Menzio and Shi (2011). As we will show, both these variants will be critical for accounting for both the macro and micro evidence on unemployment and wage dynamics.

Below we describe the labor market of the model conditional. We defer to the appendix a description of the full general equilibrium.

3.1 Search, Vacancies, and Matching

There is a continuum of firms and a continuum of workers, each of measure unity. Workers within a firm are either good matches or bad matches. A bad match has a productivity level that is only a fraction ϕ of that of a good match, where $\phi \in (0, 1)$. Let n_t be the number of good matches within a firm that are working during period t and b_t the number of bad matches. Then the firm's effective labor force l_t is the following composite of good and bad matches:

$$l_t = n_t + \phi b_t. \quad (6)$$

Firms post vacancies to hire workers. Firms with vacancies and workers looking for jobs meet randomly (i.e., there is no directed search). The quality of a match is only revealed once a worker and a firm meet. Match quality is idiosyncratic. A match is good with probability ξ and bad with complementary probability $1 - \xi$. Hence, the outcome of a match depends neither on ex-ante characteristics of the firm or the worker. Whether or not a meeting becomes a match depends on the realization of match quality and the employment status of the searching worker.

Let $\bar{n}_t = \int_i n_t di$ and $\bar{b}_t = \int_i b_t di$ be the total number of workers who are good matches and who are bad matches, respectively, where firms are indexed by i . The total number of unemployed workers \bar{u}_t is then given by

$$\bar{u}_t = 1 - \bar{n}_t - \bar{b}_t. \quad (7)$$

We assume that each unemployed worker searches with a fixed intensity, normalized at unity. Under our parameterization, it will be optimal for a worker searching from unemployment to accept both good and matches.

There are two ways a worker leaves a match. First there is an exogenous separation

probability $1 - \nu$, which means the worker becomes unemployed at the beginning of the subsequent period. Second, if the match is not destroyed, which occurs with probability ν , the worker will search on the job. If another match is found and accepted, the worker goes to the new firm within the period. Otherwise the worker remains with the firm for another period.

Absent other considerations, the only reason for an employed worker to search is to find a job with improved match quality.²⁶ In our setting, the only workers who can improve match quality are those currently in bad matches. We allow such workers to search with variable intensity ς_{bt} . As has been noted in the literature, however, not all job transitions involve positive wage changes (see Tjaden and Wellschmied, 2014). Accordingly, we suppose that workers in good matches may occasionally leave for idiosyncratic reasons, e.g. locational constraints.²⁷ We assume that these workers search with fixed intensity ς_n and accept good or bad matches. This is equivalent to a reallocation shock whereby workers in good matches are forced to search on the job with probability ς_n . It is also similar to a reallocation shock à la Moscarini and Postel-Vinay (2016) that moves employed workers to another job drawn randomly from the available ones.²⁸ Not only are job-to-job changes with a reduction in wages an empirical regularity, but their level and cyclicity is key for understanding the wage cyclicity of job changers via composition effects, as we show later.²⁹

²⁶Strictly speaking, with staggered wage contracting, workers may want to search to find a job of the same quality if their wages are (i) sufficiently below the norm and are (ii) not likely to be renegotiated for some time. However, because the likelihood a worker is in this situation in our model is extremely small due to the transitory nature on average of wage differentials due to staggered contracting, expected gains from lateral movements will be tiny: A small moving cost would suffice to rule them out. Hence, we abstract from lateral movements. In the appendix, we quantify gains from lateral movements and show that they are indeed tiny.

²⁷For similar reasons, structural econometric models formulated to assess the contribution of on-the-job search to wage dispersion in a stationary setting often include a channel for exogenous, non-economic job-to-job transitions with wage drops. Examples include Jolivet, Postel-Vinay, and Robin (2006) and Lentz and Mortensen (2012).

²⁸For the sake of analytical simplicity, we only consider a reallocation shock for good workers. We have also worked out a version of the model where workers in bad matches are also exposed to a reallocation shock. This does not have any noticeable implication on the quantitative results. The reason is that, under our calibration strategy, the two versions of the model are close to be observationally equivalent.

²⁹Several facts involving the distribution of wages for workers making job-to-job transitions are consistent with our modeling assumptions. While in our data the average wage changes of job-changers is modest – plus 4.5 percent, from the first column of Table 2 – the conditional wage changes are considerably larger in magnitude, equal to plus 26 percent for the 52 percent share of workers realizing wage gains and minus 21 percent for the 48 percent share of workers realizing wage losses. Hence, movements up and down the job-ladder involve large gains and losses, making our two-quality modeling assumption a reasonable one. Moreover, workers making match-improving job-to-job changes leave systematically lower-paying jobs. We recover the log wage residuals from a simple Mincer wage regression of log wages on observables. The average log wage residual on the prior job for job-changers moving to a higher-paying job is -0.191 , indicating that wage-improving job-changers are strongly selected from the population of workers earning lower wages than would be predicted by observable characteristics. This form of selection is consistent with a notion of “active search”, whereby the workers with the most to gain have greater incentive to invest effort in potentially costly search. Meanwhile, the average wage residual of job-changers realizing a decrease in wages is more centered

We derive the total efficiency units of search \bar{s}_t as a sum of searchers weighted by the search intensity of their respective type:

$$\bar{s}_t = \bar{u}_t + \nu(\varsigma_{bt}\bar{b}_t + \varsigma_n\bar{n}_t). \quad (8)$$

The first term reflects the effective amount of search by the unemployed (who each have search intensity normalized to unity). The second term is effect search of the employed, allowing for the difference in search intensity of bad and good matches. As we will show, the search intensity of bad matches on the job will be procyclical. Furthermore, the cyclical sensitivity of the efforts of workers in bad matches to find better jobs will ultimately be the source of procyclical movements in match quality and new hire wages.

The aggregate number of matches \bar{m}_t is a function of the efficiency weighted number of searchers \bar{s}_t and the number of vacancies \bar{v}_t , as follows:

$$\bar{m}_t = \sigma_m \bar{s}_t^\sigma \bar{v}_t^{1-\sigma}, \quad (9)$$

where σ is the elasticity of matches to units of search effort and σ_m reflects the efficiency of the matching process.

The probability p_t a unit of search activity leads to a match is:

$$p_t = \frac{\bar{m}_t}{\bar{s}_t}. \quad (10)$$

The probability the match is good p_t^n and the probability it is bad p_t^b are given by:

$$p_t^n = \xi p_t, \quad (11)$$

$$p_t^b = (1 - \xi)p_t. \quad (12)$$

The probability for a firm that posting a vacancy leads to a match q_t^m is given by

$$q_t^m = \frac{\bar{m}_t}{\bar{v}_t}. \quad (13)$$

Not all matches lead to hires, however, as workers in bad matches only accept good matches. Hires also vary by quality. The probability q_t^n a vacancy leads to a good quality hire and

around zero, with an average log wage residual of 0.044. This is consistent with the often idiosyncratic reasons for job changes such as family reasons, where a job transfer is motivated by reasons unrelated to pay.

the probability q_t^b it leads to a bad quality one are given by

$$q_t^n = \xi q_t^m, \quad (14)$$

$$q_t^b = (1 - \xi) \left(1 - \frac{\nu \varsigma_{bt} \bar{b}_t}{\bar{s}_t} \right) q_t^m. \quad (15)$$

Since all workers accept good matches, q_t^n is simply the product of the probability of a match being good conditional on a match, ξ , and the probability of a match, q_t^m . By contrast, since workers in bad matches do not make lateral movements, to compute q_t^b we must net out the fraction of searchers who search on-the-job from bad matches, $\nu \varsigma_{bt} \bar{b}_t / \bar{s}_t$.

Finally, we can express the expected number of workers in efficiency units of labor that a firm can expect to hire from posting a vacancy, q_t , as

$$q_t = q_t^n + \phi q_t^b. \quad (16)$$

It follows that the total number of new hires in efficiency units is simply $q_t \nu_t$.

3.2 Firms

Firms add labor through a search and matching process that we describe shortly. Labor in efficiency units l_t is the quality adjusted sum of good and bad matches in the firm (see equation (6)). The current value of l_t is a predetermined state.

It is convenient to define $\gamma_t \equiv b_t / n_t$ as the ratio of bad-to-good matches in the firm. We can then express l_t as the following multiple of n_t :

$$l_t = n_t + \phi b_t = (1 + \phi \gamma_t) n_t, \quad (17)$$

where as before, $\phi \in (0, 1)$ is the productivity of a bad match relative to a good one. The ratio of bad-to-good matches γ_t is also a predetermined state for the firm.

The evolution of l_t depends on the dynamics of both n_t and b_t . Letting ρ_t^i be the probability of retaining a worker in a match of type $i = n, b$, we can express the evolution of n_t and b_t as follows:

$$n_{t+1} = \rho_t^n n_t + q_t^n \nu_t, \quad (18)$$

$$b_{t+1} = \rho_t^b b_t + q_t^b \nu_t, \quad (19)$$

where $q_t^i \nu_t$ is the quantity of type i matches and where equations (14) and (15) define q_t^n and q_t^b . The probability of retaining a worker, in turn, is the product of the job survival probability ν and the probability the worker does not leave for a job elsewhere, giving the

following expressions for good and bad matches:

$$\rho_t^n = \nu(1 - s_n p_t), \quad (20)$$

$$\rho_t^b = \nu(1 - s_{bt} p_t^n), \quad (21)$$

where workers in bad matches searching on-the-job only accept good matches, while workers in good matches subject to the reallocation shock move to both good and bad matches.

It follows from equations (17), (20) and (21) that we can express the survival probability of a unit of labor in efficiency units, ρ_t , as the following convex combination of ρ_t^n and ρ_t^b :

$$\rho_t = \frac{\rho_t^n + \phi \gamma_t \rho_t^b}{1 + \phi \gamma_t}, \quad (22)$$

where we once again use γ_t to denote the ratio of bad-to-good matches.

The hiring rate in efficiency units of labor, \varkappa_t , is ratio of new hires in efficiency units $q_t v_t$ to the existing stock, l_t

$$\varkappa_t = \frac{q_t v_t}{l_t}, \quad (23)$$

where the expected number of efficiency weighted new hires per vacancy q_t is given by equation (16). The evolution of l_t is then given by:

$$l_{t+1} = (\rho_t + \varkappa_t) l_t. \quad (24)$$

It is useful to define $\bar{\gamma}_t^h \equiv (q_t^b v_t) / (q_t^n v_t) = q_t^b / q_t^n$ as the ratio bad-to-good matches among new hires. Then, making use of equations (16), (17), (18), (19) and (23) to characterize how the ratio of bad-to-good matches across all workers γ_t evolves over time, we obtain:

$$\gamma_{t+1} = \frac{\rho_t^b \gamma_t + q_t^b v_t / n_t}{\rho_t^n + q_t^n v_t / n_t} = \frac{\frac{\gamma_t}{1+\phi \gamma_t} \rho_t^b + \frac{\bar{\gamma}_t^h}{1+\phi \bar{\gamma}_t^h} \varkappa_t}{\frac{1}{1+\phi \gamma_t} \rho_t^n + \frac{1}{1+\phi \bar{\gamma}_t^h} \varkappa_t}, \quad (25)$$

where $1/(1 + \phi \gamma_t)$ is the share of good matches among incumbent workers and $1/(1 + \phi \bar{\gamma}_t^h)$ is the share of good matches among new hires and where $\gamma_t/(1 + \phi \gamma_t)$ and $\bar{\gamma}_t^h/(1 + \phi \bar{\gamma}_t^h)$ are the complementary shares of bad matches.

We now turn to the firm's decision problem. Let a_t be the productivity of an efficiency unit of labor, $\Lambda_{t,t+1}$ be the firm's stochastic discount factor and w_t be the wage per efficiency unit of labor. Assume that labor recruiting costs are quadratic in the hiring rate for labor in efficiency units, \varkappa_t , and homogeneous in the existing stock l_t . Then the firm's decision problem is to choose the hiring rate \varkappa_t to maximize the firm's value (the discounted stream of profits net recruiting costs) subject to the equations that govern the laws of motion for

labor in efficiency units l_t and the ratio of bad-to-good matches within the firm γ_t , given the expected paths of wages.

Since the firm's value $F_t(l_t, \gamma_t, w_t) \equiv F_t$ is homogeneous in l_t , we express the value of each firm per efficiency unit of labor $J_t(\gamma_t, w_t) \equiv J_t = F_t/l_t$ as

$$J_t = \max_{\varkappa_t} \left\{ a_t - \frac{\kappa}{2} \varkappa_t^2 - w_t + (\rho_t + \varkappa_t) E_t \{ \Lambda_{t,t+1} J_{t+1} \} \right\}, \quad (26)$$

subject to equation (25), given the values of firm-level states for labor composition and contract wage (γ_t, w_t) and the aggregate state vector.³⁰ For the time being, we take the firm's expected wage path as given. In Section 3.4 we describe how wages are determined for both good and bad workers.

The first order condition for hiring is

$$\kappa \varkappa_t = E_t \left\{ \Lambda_{t,t+1} \left[J_{t+1} + (\rho_t + \varkappa_t) \left[\frac{\partial J_{t+1}}{\partial \gamma_{t+1}} + \frac{\partial J_{t+1}}{\partial w_{t+1}} \frac{\partial w_{t+1}}{\partial \gamma_{t+1}} \right] \frac{\partial \gamma_{t+1}}{\partial \varkappa_t} \right] \right\}. \quad (27)$$

The expression on the left is the marginal cost of adding worker, and the expression on the right is the discounted marginal benefit. The first term on the right-hand side of (27) is standard: it reflects the marginal benefit of adding a unit of efficiency labor. The second term reflects a “composition effect” of hiring. While the firm pays the same recruitment costs for bad and good workers (in quality adjusted units), bad workers have separate survival rates within the firm due to their particular incentive to search on-the-job. The composition term reflects the effect of hiring on period-ahead composition, and the implied effect on the value of a unit of labor quality to the firm.³¹

3.3 Workers

We next construct value functions for unemployed workers, workers in bad matches, and workers in good matches. These value functions will be relevant for wage determination, as we discuss in the next section. Importantly, they will also be relevant for the choice of search intensity by workers in bad matches who are looking to upgrade.

We begin with an unemployed worker: Let U_t be the value of unemployment, V_t^n the value of a good match, V_t^b the value of a bad match, and u_B the flow benefit of unemployment. Then, the value of a worker in unemployment satisfies

$$U_t = u_B + E_t \left\{ \Lambda_{t,t+1} \left[p_t^n \bar{V}_{t+1}^n + p_t^b \bar{V}_{t+1}^b + (1 - p_t) U_{t+1} \right] \right\}, \quad (28)$$

³⁰The firm's decision problem is formulated according to the following intra-period timing protocol: (i) realization of aggregate and firm-level shocks, (ii) wage bargaining and production, (iii) realization of match-level separation shocks, and (iv) search and matching.

³¹ Under our calibration, the effect will be zero, up to a first order. See the appendix for details.

where $p_t^n = \xi p_t$, $p_t^b = (1 - \xi)p_t$, p_t is given by (10), and where \bar{V}_{t+1}^n and \bar{V}_{t+1}^b are the average values of good and bad matches at time $t + 1$.³²

For workers that begin the period employed, we suppose that the cost of searching as a function of search intensity is given by

$$c(\varsigma_{it}) = \frac{\varsigma_0}{1 + \eta_\varsigma} \varsigma_{it}^{1 + \eta_\varsigma}$$

where $i = b, n$. As we discussed earlier, workers in bad matches search on the job with variable intensity ς_{bt} in order to upgrade match quality. In contrast, a worker already in good match only moves if a “relocation” shock occurs and searches with fixed intensity ς_n .³³

Let w_{it} be the wage of a type i worker, $i = b, n$. The value of a worker in a bad match $V_t^b(\gamma_t, w_t) \equiv V_t^b$ is given by

$$\begin{aligned} V_t^b = \max_{\varsigma_{bt}} & \left\{ w_{bt} - \nu c(\varsigma_{bt}) + E_t \left\{ \Lambda_{t,t+1} \left[\nu(1 - \varsigma_{bt} p_t^n) V_{t+1}^b \right. \right. \right. \\ & \left. \left. \left. + \nu \varsigma_{bt} p_t^n \bar{V}_{t+1}^n + (1 - \nu) U_{t+1} \right] \right\} \right\} \end{aligned} \quad (29)$$

The flow value is the wage w_{bt} net the expected costs of search. If the worker “survives” within the firm, which occurs with probability ν , he searches with variable intensity ς_{bt} . The first term in the continuation value is the value of continuing in the match, which occurs with probability $\nu(1 - \varsigma_{bt} p_t^n)$. The second term reflects the value of switching to a good match, which occurs with probability $\nu \varsigma_{bt} p_t^n$. The final term reflects the value of being separated into unemployment.³⁴

A worker in the bad match chooses the optimal search intensity ς_{bt} according to (29), satisfying

$$\varsigma_0 \varsigma_{bt}^{\eta_\varsigma} = E_t \left\{ \Lambda_{t,t+1} p_t^n \left(\bar{V}_{t+1}^n - V_{t+1}^b \right) \right\} \quad (30)$$

Search intensity varies positively with the product of the likelihood of finding a good match, p_t^n , and the net gain of doing so, i.e. the difference between the value of good and bad matches. One can see from equation (30) how the model can generate procyclical search

³²Technically, the average value of employment in the continuation value of U_t should be that of a new hire rather than the unconditional one. However, Gertler and Trigari (2009) show that the two are identical up to a first order. Hence, we use the simpler formulation for clarity. In particular, the unconditional average value for a type i match is $\bar{V}_{t+1}^i = \int V_{t+1}^i(\gamma, w) dG_{t+1}(\gamma, w)$, where G denotes the joint distribution of wages and composition, while the average value conditional on being a new hire is given by $\bar{V}_{\varkappa, t+1}^i = \int V_{t+1}^i(\gamma, w) (\varkappa_t(\gamma, w) / \bar{\varkappa}_t) dG_t(\gamma, w)$, where $\bar{\varkappa}_t = \int \varkappa_t(\gamma, w) dG_t(\gamma, w)$. Since w , γ and \varkappa in the steady state are identical across firms, $\bar{V}_{\varkappa, t+1}^i = \bar{V}_{t+1}^i$ up to a first order.

³³In writing the value of a bad match, we assume that workers choosing how intensively to search on the job can expect they will not want to voluntarily make a lateral movement, i.e., a movement to another bad match. As noted in footnote 26, the expected gain from a lateral move is quantitatively trivial and can be ruled out almost surely with a small moving cost, as we show in the appendix.

³⁴Note, the state variables that enter the worker’s problem are the same as those for the firm: the ratio of bad-to-good workers within the firm γ_t and the contract wage w_t .

intensity by workers in bad matches. The probability of finding a good match will be highly procyclical and the net gain roughly acyclical. Thus, the expected marginal gain from search will be highly procyclical, leading to procyclical search intensity.

The value of a worker in a good match $V_t^n(\gamma_t, w_t) \equiv V_t^n$ is similar to the value function for a bad match.

$$\begin{aligned} V_t^n = & w_{nt} - \nu c(\varsigma_n) + E_t \left\{ \Lambda_{t,t+1} \left[\nu(1 - \varsigma_n p_t) V_{t+1}^n \right. \right. \\ & \left. \left. + \nu \varsigma_n \left(p_t^n \bar{V}_{t+1}^n + p_t^b \bar{V}_{t+1}^b \right) + (1 - \nu) U_{t+1} \right] \right\} \end{aligned} \quad (31)$$

As we discussed earlier, a worker in a good match who receives a reallocation shock may wind up moving to a bad match.

In the absence of direct evidence of the broader relation of job quality and match retention, we assume that the retention rates of good and bad matches are identical on average (implying that, in the steady state, $\xi_{\varsigma_{bt}} = \varsigma_n$). As we show in the appendix, this assumption will also be important for maintaining tractability of the firm's and workers' problem.³⁵

3.4 Nash Wage

As in GT, workers and firms divide the joint match surplus via staggered Nash bargaining. For simplicity, we assume that the firm bargains with good workers for a wage. Bad workers then receive the fraction ϕ of the wage for good workers, corresponding to their relative productivity. Thus if w_t is the wage for a good match within the firm, then ϕw_t is the wage for a bad match. It follows that w_t corresponds to the wage per unit of labor quality. We note that this simple rule for determining wages for workers in bad matches approximates the optimum that would come from direct bargaining.³⁶

Our assumptions are equivalent to having the good workers and firms bargain over the wage per unit of labor quality w_t . For the firm, the relevant surplus per worker is J_t , as shown in equation (26) of Section 3.2. For good workers, the relevant surplus is the difference between the value of a good match and unemployment:

$$H_t = V_t^n - U_t \quad (32)$$

³⁵ Two studies of job tenure and match quality over the business cycle are Bowlus (1995) and Mustre-del-Rio (2017). We note that our model is consistent with their findings on the cyclicalities of job tenure as a function of the aggregate state at match formation. In particular, Mustre-del-Rio shows that workers hired from non-employment who subsequently make a job-to-job transition have shorter tenure during expansions, consistent with the prediction of our model.

³⁶ This simple rule differs slightly due mainly to differences in duration of good and bad matches with firms. The gain from imposing this simple rule is that we need only characterize the evolution of a single type of wage. Importantly, in bargaining with good workers, firms also take account of the implied costs of hiring bad workers.

As in GT, the expected duration of a wage contract is set exogenously. At each period, a firm faces a fixed probability $1 - \lambda$ of renegotiating the wage. With complementary probability, the wage from the previous period is retained. The expected duration of a wage contract is then $1/(1 - \lambda)$.³⁷ Workers hired in between contracting periods receive the prevailing firm wage per unit of labor quality w_t . Thus in the model there is no new hire effect: Adjusting for relative productivity the wages of new hires are the same as for existing workers.

Let w_t^* denote the wage per unit of labor quality of a firm renegotiating its wage contract in the current period.³⁸ The wage w_t^* is chosen to maximize the Nash product of a unit of labor quality to a firm and a worker in a good match, given by

$$H_t^\eta J_t^{1-\eta} \quad (33)$$

subject to

$$w_{t+1} = \begin{cases} w_t & \text{with probability } \lambda \\ w_{t+1}^* & \text{with probability } 1 - \lambda \end{cases} \quad (34)$$

where w_{t+1}^* is the wage chosen in the next period if the parties are able to re-bargain and where η is the households relative bargaining power.

Let $H_t^* \equiv H_t(\gamma_t, w_t^*)$ and $J_t^* \equiv J_t(\gamma_t, w_t^*)$ (where $H_t \equiv H_t(\gamma_t, w_t)$ and $J_t \equiv J_t(\gamma_t, w_t)$).³⁹ Then the first order condition for w_t^* is given by

$$\chi_t^* J_t^* = (1 - \chi_t^*) H_t^* \quad (35)$$

where

$$\chi_t^* = \frac{\eta}{\eta + (1 - \eta) \mu_t^* / \epsilon_t^*}$$

with

$$\epsilon_t^* = \frac{\partial H_t^*}{\partial w_t^*} \quad \text{and} \quad \mu_t^* = \frac{\partial J_t^*}{\partial w_t^*}$$

Equation (35) is a variation of the conventional sharing rule, where the relative weight χ_t depends not only on the worker's bargaining power η , but also on the differential firm/worker horizon, reflected by the term μ_t / ϵ_t as discussed in GT.⁴⁰

³⁷ We use the Calvo formulation of staggered contracting for convenience, since it does not require keeping track of the distribution of remaining time on the contracts. We expect very similar results from using Taylor contracting, where contracts are of a fixed duration. An advantage with Taylor contracting is that wages are less likely to fall out of the bargaining set, since with Calvo a small fraction of firms may not adjust wages for a long time. Nonetheless, given that the broad insights from Calvo and Taylor contracting are very similar, we stick with the simpler Calvo formulation.

³⁸ We suppress the dependence of w^* and similar objects on the firm's composition in the notation.

³⁹ Recall, γ_t gives the ratio of bad-to-good workers within a firm.

⁴⁰ Intuitively, when valuing the contract wage stream, the firm has a longer horizon than the worker because it cares about the effect of the current wage contract on payments not only to the existing workforce,

Under multi-period bargaining, the outcome depends on how the new wage settlement affects the relative surpluses, J_t^* and H_t^* , in subsequent periods where the contract is expected to remain in effect. The net effect, as shown in GT, is that up a first order approximation the contract wage will be an expected distributed lead of the target wages that would arise under period-by-period Nash bargaining, where the weights on the target for period $t + i$ depend on the likelihood the contract remains operative, λ^i .

To a first order, we can express the evolution of average wages \bar{w}_t as

$$\bar{w}_t = (1 - \lambda)\bar{w}_t^* + \lambda\bar{w}_{t-1} \quad (36)$$

where $1 - \lambda$ is the fraction of firms that are renegotiating and λ is the fraction that are not and where the average wage and the average contract wage per unit of labor quality are defined by

$$\bar{w}_t = \int_{w,\gamma} w dG_t(\gamma, w) \quad (37)$$

$$\bar{w}_t^* = \int_{w,\gamma} w_t^*(\gamma) dG_t(\gamma, w) \quad (38)$$

with $G_t(\gamma, w)$ denoting the time t fraction of units of labor quality employed at firms with wage less than or equal to w and ratio of bad-to-good workers less than or equal to γ . (See the appendix for details.)

4 New Hire Wages, Match Quality and Job-to-Job Flows

We now show how cyclical composition allows our framework to generate the appearance of excess new hire wage cyclicity, even though within the model new hire wages are no more flexible than those of existing workers. In doing so, we demonstrate how our model framework developed in Section 3 maps into the canonical Bils' regression from the empirical literature. To do so we derive an expression for the average wage growth of job changers that permits us to interpret estimates of job changer wage cyclicity from the data. In the process, we relate the full model to the approximate DGM that we developed in Section 2 to interpret our reduced form empirical results.

Let \bar{g}_t^w denote the average wage growth of continuing workers, \bar{g}_t^{EE} the average wage growth of new hires who are job changers, and $\Delta\bar{\alpha}_t^{EE}$ the component of \bar{g}_t^{EE} due compositional effects (i.e. changes in match quality across jobs). Further, let $\delta_{BG,t}$ be the share of flows moving from bad to good matches out of total job flows at time t and $\delta_{GB,t}$ the

but also to the new workers who enter under the terms of the existing contract. A worker, on the other hand, only cares about wages during his or her tenure at the firm. While the horizon effect is interesting from a theoretical perspective, GT shows that it is quantitatively miniscule, implying χ_t is very close to η .

share moving from good to bad matches.⁴¹ Then we can express the average wage growth for job-changers as the following:

$$\bar{g}_t^{EE} = \bar{g}_t^w + \Delta \bar{\alpha}_t^{EE} \quad (39)$$

with

$$\bar{g}_t^w = \log \bar{w}_t - \log \bar{w}_{t-1} \quad (40)$$

and

$$\Delta \bar{\alpha}_t^{EE} = (-\log \phi) (\delta_{BG,t-1} - \delta_{GB,t-1}). \quad (41)$$

As in the approximate DGM, we see from equation (39) that the wage growth of job-changers is additively separable in two components: a common component equal to average wage growth of continuing workers, as described in equation (40); and a separate component $\Delta \bar{\alpha}_t^{EE}$, described in equation (41), that serves as the model analogue for the average change in match quality for job-changers under equation (3) of the approximate DGM.

Equation (41) indicates that a fraction $\delta_{BG,t-1}$ of job-changers realizes wage gains of $(-\log \phi)$ at t , a fraction $\delta_{GB,t-1}$ realizes wage losses of $(-\log \phi)$ at t , and the remaining fraction realizes no change at all. Absent the composition effect (i.e. if $\phi = 1$), average wage growth for job changers would look no different than for continuing workers. With the composition effect present, however, cyclical variation of match quality will enhance the relative cyclicity of job changers wages, as we discuss next.

We first note that, absent cyclical fluctuations, the average change in match quality is given by the term $(-\log \phi) (\tilde{\delta}_{BG} - \tilde{\delta}_{GB})$, where \tilde{z} denotes the steady state value of a variable z_t . This term is analogous to the coefficient ψ_n^{EE} in equation (3) of the approximate DGM, which describes the non-cyclical component of changes in match quality for job-changers.

The change in average match quality for job changers also has a cyclical component whose dynamic behavior is function of the dynamics of the flow shares $\delta_{BG,t}$ and $\delta_{GB,t}$. As might be expected, this is where the mapping of the model to the approximate DGM becomes more complicated. Whereas the change in average match quality for job changers is proportional to the change in the unemployment rate in the approximate DGM, in the full model the dependence will be expressed more generally in terms of changes in variables

⁴¹ The model includes two types of job-to-job movers: those who search with variable search intensity from bad matches and those in good matches who are forced to search for non economic reasons, i.e., who are subject to a reallocation shock. Since workers in bad matches searching on the job only accept good matches, the first type of job changers leads only to bad-to-good flows, $\nu_{\zeta_{bt}} \xi p_t \bar{b}_t$. The second type of job changers instead leads to both good-to-bad and good-to-good flows, $\nu_{\zeta_n} (1 - \xi) p_t \bar{n}_t$ and $\nu_{\zeta_n} \xi p_t \bar{n}_t$. Importantly, job-to-job changes with either no appreciable change in wages or with a reduction in wages are important not only for matching empirical evidence, but also for understanding the wage cyclicity of job changers via composition effects. Later, we use empirical moments on the level and cyclicity of the share of bad-to-good flows out of total job flows to discipline the calibration of the model.

describing the composition of match quality in the aggregate labor market. This relation emerges from the search decision of workers in bad matches.

Specifically, loglinearizing the compositional component of job changers wage growth, after substituting the expressions for the flow shares $\delta_{BG,t-1}$ and $\delta_{GB,t-1}$ (see the appendix for details), gives:

$$\widehat{\Delta \bar{\alpha}_t}^{EE} = \alpha_1 \widehat{\bar{\varsigma}_{bt-1}} + \alpha_2 \widehat{\bar{\gamma}_{t-1}}, \quad (42)$$

where \widehat{z}_t denotes log deviations of variable z_t from steady state and where the parameters α_1 and α_2 are positive and functions of model primitives. As we have discussed, the search intensity by workers in bad matches, $\bar{\varsigma}_{bt-1}$, is highly procyclical, leading to $\delta_{BG,t-1}$ being procyclical and $\delta_{GB,t-1}$ countercyclical. The dynamics of the shares, and thus the dynamics of changes in match quality, also depend on the relative stocks of bad and good matches available to make a job-to-job transition, as measured by $\bar{\gamma}_{t-1}$. As we show in the next section, while the aggregate ratio of bad-to-good matches $\bar{\gamma}_{t-1}$ is countercyclical, the net quantitative effect leads to procyclical composition. At the beginning of a boom, search intensity $\bar{\varsigma}_{bt-1}$ increases, generating a positive change in average match quality. Only in the latter phase of an expansion does the reduction of workers in bad matches available to make a bad-to-good change overshadow the effect on composition of the increase in search intensity among workers in bad matches. In order to make the connection between the cyclical component of average match quality in the full model and the cyclical component in the approximate DGM, we next show that equation (42) implies a relation between the change in match quality and the change in the unemployment rate that well approximates the exact proportional relation imposed in the DGM.

To do so, we first note that the dynamic evolution of the ratio of bad to good matches, $\bar{\gamma}_t$, implies the following relation between search intensity by workers in bad matches, $\bar{\varsigma}_{bt-1}$, and the change in $\bar{\gamma}_t$ relative to both $\bar{\gamma}_{t-1}$ and $\bar{\gamma}_{t-1}^h$ (where the latter is the ratio of bad to good matches among new hires at $t-1$):

$$(\nu - \tilde{\rho}) \widehat{\bar{\varsigma}_{bt-1}} = -\rho (\widehat{\bar{\gamma}_t} - \widehat{\bar{\gamma}_{t-1}}) - (1 - \tilde{\rho}) (\widehat{\bar{\gamma}_t} - \widehat{\bar{\gamma}_{t-1}^h}). \quad (43)$$

We then note that simply using the definition of the unemployment rate we can write the change in the ratio of bad-to-good matches from $t-1$ to t as a linearly increasing function of the change in the unemployment rate from $t-1$ to t :

$$\widehat{\bar{\gamma}_t} - \widehat{\bar{\gamma}_{t-1}} = \frac{\tilde{u}}{\tilde{n}} (\widehat{u_t} - \widehat{u_{t-1}}) + \frac{1 - \tilde{u}}{\tilde{n}} (\widehat{b_t} - \widehat{b_{t-1}}). \quad (44)$$

It is easy to see that combining equation (42) with equations (43) and (44) gives an expression that relates $\widehat{\Delta \bar{\alpha}_t}^{EE}$ to Δu_t , consistently with the DGM. However, the relation

is not exact, due to the presence of other terms related to the composition of the labor force. Further, the dynamics of these terms will be jointly determined with the dynamics of unemployment, implying that neither the set of estimated coefficients from the canonical regression nor those of our new regression equation permit a clear structural interpretation. Hence, we shift to a quantitative focus.

Specifically, in the next section, we show that the net effect of procyclical search intensity $\widehat{\zeta}_{bt-1}$ and countercyclical bad-to-good match quality $\widehat{\gamma}_{t-1}$, as described in (42), is that $\Delta \bar{\alpha}_t^{EE}$ is procyclical. That is, the composition effect for job changers enhances measured wage growth during expansions and weakens it during recessions. In this way the model can replicate the kind of cyclical movements in match quality that can lead to estimates of new hire wage cyclicalities that suffer from the kind of composition bias we discussed in Section 2. We demonstrate this concretely in the next section by showing that data generated from the model will generate estimates of a new hire effect on wages for job changers, even as new hires' wages are no more flexible than those of existing workers.

5 Results

In this section we present some simulations to show how the model can capture both the aggregate evidence on unemployment fluctuations and wage rigidity and the panel data evidence on the relative cyclicalities of new hires' versus continuing workers' wages. We first describe the calibration before turning to the results.

5.1 Calibration

We adopt a monthly calibration. There are 16 parameters in the model for which we must select values. We calibrate 9 of the parameters using external sources. Five of the externally calibrated parameters are common to the macroeconomics literature: the discount factor, β ; the capital depreciation rate, δ ; the “share” of labor in the Cobb-Douglas production technology, ζ ; and the autoregressive parameter and standard deviation for the total factor productivity process, ρ_z and σ_z (see Section C.1 in the appendix). Our parameter choices are standard: $\beta = 0.99^{1/3}$, $\delta = 0.025/3$, $\zeta = 1/3$, $\rho_z = 0.95^{1/3}$, and $\sigma_z = 0.007$.^{42,43}

Four more parameters are specific to the search literature. We assume a Cobb-Douglas matching function, and our choice of the matching function elasticity with respect to

⁴² Note that, in contrast to the frictionless labor market model, the term ζ does not necessarily correspond to the labor share, since the labor share will in general depend on the outcome of the bargaining process. However, because a wide range of values of the bargaining power imply a labor share just below ζ , here we simply follow convention by setting $\zeta = 1/3$.

⁴³ The parameter σ_z is chosen to target the standard deviation of output.

searchers, σ , is 0.4, guided by the estimates from Blanchard and Diamond (1989). We set the worker's bargaining power η to 0.5, as in GT. We normalize the matching function constant, σ_m , to 1.0. We choose λ to target the average frequency of wage changes. Taylor (1999) argues that medium to large-size firms adjust wages roughly once every year; this is validated by findings from microdata by Gottschalk (2005), who concludes that wages are adjusted roughly every year. We set $\lambda = 11/12$, implying an average duration between negotiations of twelve months. The parameter values are given in Table 6.

The remaining seven parameters are jointly calibrated to match model-relevant moments measuring average transition probabilities, individual-level wage dynamics, and the value of leisure. We calibrate the inverse productivity premium, ϕ ; the probability that a new match is good, ξ ; the elasticity of the search cost, η_ζ ; the hiring cost parameter, κ ; the separation probability, $(1 - \nu)$; the scale parameter of the search cost, ς_0 ; and the flow value of unemployment, u_B , to match seven moments: the average wage change of workers making EE transitions; the average share of bad-to-good flows out of total job flows; the cyclicalities of the share of bad-to-good flows; the average UE probability; the average EU probability; the average EE probability; and the relative value of non-work. Although there is not a one-to-one mapping of parameters to moments, there is a sense in which the identification of particular parameters are more informed by certain moments than others. We use this informal mapping to provide a heuristic argument of how the various parameters are identified.

We calibrate ϕ to target the average wage change of workers making direct job-to-job transitions in our data, 4.5 percent (see Table 2, column 1); holding everything constant, a higher ϕ implies a smaller (positive) average percentage wage increase for job changers. We recover $\phi = 0.78$. We calibrate ξ to match the average share of job transitions involving positive wage changes out of total job flows in our data, 0.52. Holding fixed the targeted transition probabilities, a lower ξ corresponds to a higher steady state value of bad-to-good workers $\tilde{\gamma}$, and hence a higher average share of bad-to-good flows. We recover $\xi = 0.30$. We calibrate η_ζ to match the cyclicalities of the share of bad-to-good flows, measured as the coefficient from a regression of the bad-to-good flow share on unemployment;⁴⁴ a higher η_ζ corresponds to a lower elasticity of search intensity to changes in the expected gain from

⁴⁴ We first create an indicator variable, $I\{BG_{it} = 1\}$ which takes on a value of one if a worker who changes jobs receives a pay increase and zero otherwise. We then regress the indicator on a first difference of individual characteristics and the unemployment rate, as follows:

$$I\{BG_{it} = 1\} = \pi_c + \Delta x'_{it}\pi_x + \eta_{BG} \cdot u_t + \varepsilon_{it}$$

The coefficient η_{BG} tells how the share of workers that improve wages varies with the unemployment rate. Our point estimate of η_{BG} is -1.35 , significant at the one percent level. The estimate suggests that if the unemployment rate increases by one percentage point, the share of workers that are upgrading their jobs drops by 0.0135 percentage points, consistent with a procyclical share of job-changers moving to jobs with better pay.

on-the-job search (see equation (30)), and thus, other things equal, to a lower cyclical-ity of bad-to-good flows. We obtain $\eta_\varsigma = 1.14$.⁴⁵

We calibrate the separation probability $(1 - \nu)$ to match the empirical EU probability of 0.025. The hiring cost parameter κ determines the resources that firms place into recruiting, and hence, influences the probability that a worker finds a job. We set the steady state job finding probability \tilde{p} to match the monthly UE transition probability, 0.42; and then calibrate κ to be consistent with \tilde{p} . We restrict $\varsigma_n = \xi \tilde{\varsigma}_b$ to have on average equal retention rates for workers in good and bad matches and note that a higher search cost implies a lower EE probability. We calibrate ς_0 to match an EE probability of 0.025; we obtain $\varsigma_0 = 2.15$.⁴⁶

We interpret the flow value of unemployment u_B as capturing both unemployment insurance and utility of leisure. We calibrate u_B to target a relative value of nonwork to work activity \bar{u}_T equal to 0.71 as in Hall and Milgrom (2008). In our setting, the relative value of nonwork activities satisfies

$$\bar{u}_T = \frac{u_B + \nu c(\varsigma_n)}{\tilde{a} + (\kappa/2)\tilde{\chi}^2},$$

where $\tilde{a} = (1 - \zeta)\tilde{y}/\tilde{l}$. Note that the value of nonwork includes saved search costs from on-the-job search and the value of work includes saved vacancy posting costs. Finally, when taking the model to the data, we assume that workers in less productive matches receive a period surplus proportional to that of more productive matches by a factor ϕ , through a lower disutility of labor.⁴⁷ In doing so, we ensure that workers in bad matches always receive positive surplus from employment.

The full list of parameter values and targeted moments are given in Table 7. Having fully calibrated the model, we now evaluate whether it provides an accurate description of aggregate and individual-level dynamics. We first test the ability of the model to match the cyclical properties of aggregate unemployment and wages. Second, we assess the ability of the model to generate the correct relative cyclical-ity in wage growth for job changers versus continuing workers.

5.2 Model Simulations of Aggregate and Panel Data Evidence

We first explore whether the model provides a reasonable description of labor market volatility. In particular, we compare the model implications to quarterly U.S. data from 1964:1 to 2013:2. We take quarterly averages for monthly series in the data. Given that the model is

⁴⁵ This is close to a quadratic search cost function parameterization and similar to Lise (2013) and Christensen *et al.* (2005).

⁴⁶ The values for the EU, EE and UE probabilities are from Lise and Robin (2017).

⁴⁷ This is similar to Postel-Vinay and Robin (2002) and others, who assume that the worker surplus is linear in the idiosyncratic productivity of the worker.

calibrated to a monthly frequency, we take quarterly averages of the model simulated data series.

We measure output y as real output in the nonfarm business sector. The wage w is average per worker earnings of production and non-supervisory employees in the private sector, deflated with the PCE. Total employment $n + b$ is measured as all employees in the nonfarm business sector. Unemployment u is civilian unemployment 16 years and older. Vacancies v are a composite help-wanted index computed by Barnichon (2010) combining print and online help-wanted advertising. The data and model output are detrended with an HP filter with the conventional smoothing parameter.

To explore how the model works to capture the aggregate data, we first compute impulse responses to a one percent shock to productivity. To highlight the role of staggered wage contracting, we compute the model generated output for the staggered case and the flexible wage case. The model with wage rigidity produces an enhanced response of output and the various labor market variables, relative to the flexible wage case. This result is standard in the literature dating back to Shimer (2005) and Hall (2005) and in close keeping with Gertler and Trigari (2009), who use a similar model of staggered wage contracting, but without variable match quality or on-the-job search with endogenous search intensity. Our results confirm that these additional model elements do not alter the main implications of wage rigidity for aggregate dynamics. Given these basic features, we then compute a variety of business cycle moments obtained from stochastic simulation obtained from feeding in a random sequence of productivity shocks.

The impulse responses to a one percent increase in productivity are plotted in Figure 2. The solid line is the response of the baseline model with staggered wage contracting and the dashed line is the model with period-by-period Nash bargaining. Under period-by-period contracting, the model implications are reminiscent of those of the standard Nash bargaining model discussed by Hall (2005) and Shimer (2005). Wages immediately increase following a technology shock, whereas employment, unemployment, and vacancy posting respond only gradually and moderately. In the case with staggered contracting, the pattern is reversed: wages adjust gradually and only modestly, whereas there are greater changes in employment and unemployment. These are to a great extent the result of larger increases in vacancies and the job-finding probability under staggered bargaining. Additionally, we see that for both period-by-period and staggered bargaining, the stock of workers in good matches increases while the stock of workers in bad matches decreases; however, the quantitative magnitude of the change is greater for the economy with staggered bargaining.

Table 8 compares the various business cycle statistics and measures of labor market volatility generated by the model with the data. The top panel gives the empirical standard deviations, autocorrelations, and correlations with output of wages, employment, un-

employment, and vacancies. All standard deviations are normalized relative to output. The bottom panels compute the same statistics using the model. We simulate the model for recontracting on average every four quarters and continuous recontracting.

Overall, the model does a reasonable job of accounting for the relative volatility of unemployment (4.56 in the model versus 5.74 in the data) and for wages (0.47 versus 0.48). As is common in the literature, the model understates the volatility of employment; here, the absence of a labor force participation margin is relevant. Consistent with Shimer (2005) and Hall (2005), the wage inertia induced by staggered contracting is critical for the ability of the model to account for the volatility of unemployment. This result is robust to allowing for on-the-job search and procyclical match quality.

We next turn to the model’s ability to account for the panel data evidence. We simulate the model to generate a panel for unemployment rates and wages of new hires and continuing workers.⁴⁸ We then use the simulated data to perform two validation checks. First, we run the regression in equation (1), where we estimate a single term for new hire wage cyclicality. Second, we compute the coefficients in equation (5), where we allow separate terms for new hires from employment and non-employment. Both equations are estimated on model simulated data using both a first-differences and a fixed-effects estimator and compared to the SIPP estimates.

Results for the first exercise are given in Table 9, where we compare the results from the SIPP panel data (the first column for first differences and the fourth column for fixed effects) with those obtained from data from our model with wage contracts fixed for four quarters on average (the second and fifth columns), and flexible wages (the third and sixth columns). When estimated in first differences, the calibrated model with staggered contracting generates (untargeted) wage semi-elasticities remarkably similar to the coefficient estimates from the SIPP, for both continuing workers (-0.51 in the model versus -0.46 in the data) and new hires (-1.08 versus -1.13). The estimated excess wage cyclicality for new hires, however, is an artifact of cyclical composition bias, as wages for new hires in the model are no more flexible than wages of continuing workers (as illustrated by the structural equations we have developed in Section 4). The model also replicates the patterns in the data when using a fixed-effects estimator, though the quantitative match between the model and the data is less precise,

In columns three and six, we explore the implications of period-by-period Nash bargain-

⁴⁸ We generate a simulated panel of six three-month waves from our model to replicate our sample from the SIPP. Note, although the simulated panel will match the frequency of *EE*, *EU*, and *UE* transitions, the simulated panel will not generically match the frequency of workers who ever report being a new hire while they are followed by the SIPP. This is due to a multitude of reasons, including sample exclusion restrictions that we make for our empirical analysis and lifecycle patterns that are beyond the scope of the model. To correct for this discrepancy, we employ sampling weights for the simulated data so that the simulated panel matches the fraction of workers who are ever *EE*, ever *ENE*, and never *ENE* or *EE* in the SIPP.

ing for wage determination. Although the model generates a new hire effect, the estimated wage elasticities are too large. Thus, to account for the panel data estimates it is necessary to have not only procyclical movements in new hires' match quality but also some degree of wage inertia as, for example, produced by staggered multi-period contracting.

Table 10 gives results for the second exercise, where we estimate separate terms for new hires from unemployment and employment. The results show that the excess wage cyclical-ity of new hires in the model is driven by those coming from employment. The coefficient for workers making a direct employment-to-employment transition that we estimate from model simulated data is -1.86 against -1.87 estimated in the SIPP data when using first differences, and -1.11 against -1.97 when using fixed effects. For new hires from unemployment, the measure of excess wage flexibility moves close to zero. For first differences, the estimate is -0.44 (and not significant) for the SIPP versus -0.46 for the model. With fixed effects it is -0.33 (and not significant) versus -0.32 .⁴⁹

Figures 3 and 4 illustrate how compositional effects influence wage dynamics. We repeat the experiment of a one percent increase in TFP. Figure 3 then reports impulse responses for labor in efficiency units, good matches, bad matches and job flows between good and bad matches. In the wake of the boom, labor quality increases. Underlying this increase is a rise in good matches and a net fall in bad matches. The rise in good matches is due in part to good matches being hired out of unemployment. But it is mostly due to an increase in the job flow share of workers moving from bad to good matches and a decline in the reverse flow share, as the two bottom left panels indicates. This pattern in the net flows also leads to a net decline in bad matches.⁵⁰

Figure 4 then decomposes the response of job changers' wage growth into the part due to the growth of contracts wages and the part due to compositional effects, using the loglinear versions of equations (39), (40), and (41). The solid line in the top panel is total new hires' wage growth, the dashed line is the component due to composition, and the dashed line is the component due to average contract wage growth. As the figure illustrates, most of the wage response of new hires that are job changers is due to compositional effects. The bottom panel then relates the compositional effect mainly to the increase in the share of

⁴⁹ In the numerical results we thus recover a small indirect composition effect that lends additional cyclical-ity to the wage growth of new hires from unemployment. At the peak of an expansion, after unemployment has begun to return to its higher steady state level, the slow-moving average match quality is still improving. At this point, when unemployment is fast increasing, new hires from unemployment will have had higher wages on their last job, implying larger-than-average wage reductions upon re-employment. This explains the slight negative correlation between wage growth across jobs and the change in unemployment for new hires from unemployment. Note, however, that the ENE coefficient from the model is small in magnitude and falls within a one standard error confidence band of the SIPP estimates reported in Table 10. This applies to both first differences and fixed effects.

⁵⁰ In gross term there are bad matches due to workers being hired from unemployment; however, the behavior of the job-to-job flows swamps this effect.

job flows moving from bad to good matches.

6 The Marginal Cost of Labor and Composition Bias

In models with long-term firm-worker relations, the firm’s hiring decision depends on the present value of wages a new hire is expected to receive, along with hiring costs. Within this class of models, Kudlyak (2014) derives an expression for the wage component of the marginal cost of labor in terms of current and future wages, i.e. the “user cost” of labor ucl_t :

$$ucl_t = \underbrace{w_{t,t}}_{\text{hiring wage}} + E_t \underbrace{\left\{ \sum_{s=1}^{\infty} (\beta\rho)^s (w_{t,t+s} - w_{t+1,t+s}) \right\}}_{\equiv f_t} \quad (45)$$

where $w_{t,t+s}$ is the wage paid at $t+s$ to a worker hired in t , ρ is the worker survival rate, and β is the discount factor. The user cost is the sum of two components: (i) the current contract wage $w_{t,t} \equiv w_t$, and (ii) a measure of history dependence in future wages f_t , expressed as the difference between the discounted stream of wages paid from $t+1$ to a worker hired in t and the discounted stream to be paid to an identical worker hired in $t+1$. In our model — or any model of contracting whereby workers of the same characteristics within the same firm receive the same wage — f_t is equal to zero since wages are independent of the hiring date, controlling for worker/firm fundamentals. Thus in our framework the user cost of labor is simply equal to the contract wage.⁵¹ However, if wages are permanently indexed to the time that a worker is hired à la Pissarides (2009), history dependence captured by f_t will make the user cost of labor more cyclical than the hiring wage w_t .

Kudlyak (2014) and Basu and House (2017) estimate the cyclicity of the user cost of labor relative to the wages of continuing workers and new hires.⁵² Their key identifying assumption is that match quality and separation rates are invariant to the cycle. As we now argue, such an identifying assumption will conflate procyclical composition as evidence of history dependence à la Pissarides. To do so, we contrast the true user cost in equation (45) with the measured user cost ucl_t^m constructed from ex-post wages by Kudlyak (2014) and Basu and House (2017):

$$ucl_t^m = w_{t,t}^m + E_t \underbrace{\sum_{s=1}^{\infty} (\beta\rho^m)^s (w_{t,t+s}^m - w_{t+1,t+s}^m)}_{\equiv f_t^m} \quad (46)$$

⁵¹This property can be described as “equal treatment” within a firm. Note, it holds trivially in a setting with period-by-period Nash bargaining à la Shimer (2005) and Hagedorn and Manovskii (2008).

⁵²If the wages of new hires are no more cyclical than of continuing workers, the cyclicity of f_t is zero, and the cyclicity of the user cost is equal to the cyclicity of the contract wage

where $w_{t,t+s}^m$ is the average measured wage of workers at time $t + s$ who still occupy the job that they were hired into at time t , ρ^m is the average measured retention rate, and f_t^m is the measured history dependent component of the user cost. Whereas the user cost reflects the marginal cost of labor in efficiency units, the measured user cost is not adjusted for composition. If the distribution of job quality among new hires and retention rates are acyclical, as assumed by Kudlyak (2014), the cyclicity of the true user cost and the measured user cost will be the same. But under our model, where the true user cost ucl_t is simply equal to the contract wage w_t , the measured user cost will be equal to the contract wage plus a compositional term c_t^{ucl} , up to a first order. Because c_t^{ucl} is highly procyclical, it's presence will bias upward the estimate of the cyclicity of the user cost.

We express the loglinearized measured user cost of labor in our model \widehat{ucl}_t^m as the sum of the true user cost \widehat{ucl}_t and the compositional component \widehat{c}_t^{ucl} :⁵³

$$\widehat{ucl}_t^m = \widehat{ucl}_t + \widehat{c}_t^{ucl} = \widehat{w}_t + \widehat{c}_t^{ucl}. \quad (47)$$

The composition component captures both the bias in the measure in the current wage and also the bias in the measured history dependence component f_t^m . It can be expressed as

$$\widehat{c}_t^{ucl} = -\Psi \left(\widehat{\gamma}_{t-1}^h + \frac{\tilde{\rho}\beta}{1 - \tilde{\rho}\beta} \left[\left(\widehat{\rho}_t^b - \widehat{\rho}_t^n \right) + \left(\widehat{\gamma}_t^h - \widehat{\gamma}_{t-1}^h \right) \right] \right) \quad (48)$$

where γ_t^h is the bad-to-good ratio of matches among new hires at time t , ρ_t^n is the retention rate of good matches, ρ_t^b is the retention rate of bad matches, $\tilde{\rho}$ is the steady-state retention rate, and $\Psi > 0$ is a function of model primitives.

The first term in the expression for \widehat{c}_t^{ucl} reflects how procyclical match quality introduces upward bias in the measure of the cyclicity of the hiring wage at t , $w_{t,t}$: \widehat{c}_t^{ucl} varies inversely with γ_{t-1}^h , which is countercyclical.⁵⁴ The latter two terms reflect the impact of composition bias on the measured history dependent component of the user cost, f_t^m . The first term in brackets reflects a discount rate effect due to cyclical variability in the relative retention rates of workers in good and bad matches. Given that workers in bad matches are expected to leave the firm at a higher rate during expansions (and that the retention rate of workers in bad matches is more cyclical than of workers in good matches), this effect provides another source of procyclical composition bias. Finally, the second term in brackets captures how composition bias affects the future stream of wages. Given that the improvement in the composition of match quality of new hires is sufficiently cyclical and persistent, as captured by $-(\widehat{\gamma}_t^h - \widehat{\gamma}_{t-1}^h)$, this last term provides a third source of procyclical composition bias.

⁵³See the appendix for details.

⁵⁴Recall, workers are hired at the end of the period and begin as new hires the subsequent period. Hence, the ratio of bad-to-good matches among new hires at time t is given by γ_{t-1}^h .

In sum, while the true user cost ucl_t of our model is simply equal to the contract wage w_t , the measured user cost will demonstrate considerable cyclicalities due to the unmeasured compositional effects. This measured cyclicalities however does not reflect true flexibility in the user cost. To illustrate, we accordingly use our baseline model of Section 3 to simulate a time series for both the true user cost of labor, given by the hiring wage w_t ; and the measured user cost of labor, given by the sum of hiring wage w_t and the compositional component c_t^{ucl} . We calculate the semi-elasticity to unemployment of both measures and obtain -0.65 for the true user cost and -2.43 for the measured one (unadjusted for composition). Hence, the semi-elasticity of the measured user cost is almost 4 times as large as the semi-elasticity of the true user cost. This higher measured elasticity is entirely due to composition bias.⁵⁵

While one could attempt to formulate an alternative empirical representation for the measured user cost of labor that is closer to the true user cost, the main finding of our paper — that the composition-corrected wage cyclicalities of new hires is approximately equal to that of continuing workers — implies that the cyclicalities of the wage component of the marginal cost of labor can be read directly from the wage cyclicalities of workers in continuing matches.

7 Concluding Remarks

We present panel data evidence suggesting that the excess cyclicalities of new hires' wages relative to existing workers may be an artifact of compositional effects in the labor force that have not been sufficiently accounted for in the existing literature. We then use our results to draw inferences about the true flexibility of the marginal cost of labor. Key to our identification is that to a reasonable approximation, the wages of new hires from unemployment provide a composition free estimate of new hire wage flexibility. By contrast, the wages of new hires who are job changers, which account for the overall cyclicalities of new hire wages, appears to be driven entirely by procyclical job upgrading and not true wage flexibility.

We reinforce the idea that the observed excess cyclicalities of new hire wages could reflect compositions effects by developing a model of unemployment that can account for both the macro and micro data. Within the model, new hires receive the same wage as existing workers with the same fundamental characteristics (i.e., productivity, outside option). Due to this "equal treatment" of workers, there is not true excess flexibility of new hire wages. However, as we find in our estimates from panel data, new hire wages appear to be more cyclical due to the procyclicalities of job quality in new matches that stems from workers

⁵⁵ Consistently with Kudlyak's estimates, the cyclicalities of the measured user cost implied by our model is higher than the cyclicalities of new hire wages, not adjusted for composition ($= -1.59$).

changing jobs.

Indeed within our model, where workers receive “equal treatment”, the user cost of labor is simply the current wage. Since new hires and existing workers receive the same (productivity adjusted) wage, our analysis suggests that the sluggish behavior of existing workers wages may be a better guide to the true flexibility of the marginal cost of labor than the observed high cyclical of new hires wages unadjusted for composition. What all this suggests is that it is reasonable for macroeconomists to continue to make use of wage rigidity to account for economic fluctuations.

Finally, our model of unemployment fluctuations with staggered wage contracting differs from much of the DSGE literature in allowing a channel for procyclical job-to-job transitions. For many purposes, it may be fine to abstract from this additional channel. However in major recessions like the recent one, a slowdown in job reallocation is potentially an important factor for explaining the overall slowdown of the recovery. A recent study by Haltiwanger *et al.* (2018) provides evidence that the rate of job-to-job transitions has not recovered relative to the overall job-finding rate in the current recovery. Our model provides a hint about how the slowdown in job reallocation might feedback into other economic activity, by reducing overall total factor productivity. The latter can be thought of as a sullyng effect of recessions along the lines of Barlevy (2002). It might be interesting to explore this issue in more detail in subsequent research.

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Table 1: “Canonical regression” à la Bils (1985) and the new hire effect

	First differences	Fixed-effects
	(1)	(2)
Unemployment rate	−0.461*** (0.0967)	−0.147** (0.0605)
Unemp. rate · $\mathbb{I}(\text{new})$	−1.134** (0.4606)	−1.642*** (0.3263)
$\mathbb{I}(\text{new})$	0.010** (0.0040)	−0.011*** (0.0017)
No. observations	321,396	378,661
No. individuals	57,265	57,265
No. new hires	14,674	18,096

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: log hourly real wage. Controls for education, union coverage, marital status, a quadratic in tenure, and a linear time trend. Robust standard errors in parenthesis, clustered by individual.

Table 2: Job changers (EE) vs. new hires from unemployment (ENE)

	First differences		Fixed-effects	
	(1)	(2)	(3)	(4)
UR	−0.426*** (0.0967)	−0.421*** (0.0966)	−0.145** (0.0609)	−0.146** (0.0609)
UR · $\mathbb{I}(EE)$	−1.868*** (0.6793)	−1.667*** (0.6218)	−1.972*** (0.5027)	−1.933*** (0.4724)
UR · $\mathbb{I}(ENE)$	−0.437 (0.6636)	−0.547 (0.7342)	−0.334 (0.5399)	0.047 (0.5954)
$\mathbb{I}(EE)$	0.045*** (0.0048)	0.038*** (0.0046)	0.004* (0.0023)	0.001 (0.0022)
$\mathbb{I}(ENE)$	−0.047*** (0.0066)	−0.065*** (0.0074)	−0.030*** (0.0029)	−0.034*** (0.0034)
$P(\pi_{nu}^{EE} = \pi_{nu}^{ENE})$	0.127	0.239	0.023	0.008
Unemp. spell for ENE	0+	1+	0+	1+
No. observations	318,763	318,763	375,642	375,642
No. individuals	56,879	56,879	56,879	56,879
No. EE new hires	8,719	10,129	9,861	10,129
No. ENE new hires	5,333	3,923	6,439	4,860

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: log hourly real wage. Controls for education, union coverage, marital status, a quadratic in tenure, and a linear time trend. Robust standard errors in parenthesis, clustered by individual.

Table 3: EE & ENE: controls for occupation and industry switchers

	First differences		Fixed effects	
	(1)	(2)	(3)	(4)
UR	−0.424*** (0.0966)	−0.424*** (0.0966)	−0.145** (0.0610)	−0.145** (0.0609)
UR · $\mathbb{I}(EE)$	−2.635*** (0.9397)	−2.232** (0.8806)	−2.604*** (0.6131)	−2.861*** (0.6025)
UR · $\mathbb{I}(ENE)$	0.114 (0.9982)	0.310 (0.9332)	0.612 (0.7422)	0.816 (0.6777)
UR · $\mathbb{I}(EE \text{ \& switcher})$	1.299 (1.3245)	0.708 (1.3349)	1.098 (0.7262)	1.690** (0.7457)
UR · $\mathbb{I}(ENE \text{ \& switcher})$	−0.864 (1.3042)	−1.346 (1.2814)	−1.730* (0.9099)	−2.315** (0.9066)
$\mathbb{I}(EE)$	0.055*** (0.0066)	0.051*** (0.0061)	0.013*** (0.0030)	0.011*** (0.0028)
$\mathbb{I}(ENE)$	−0.007 (0.0093)	−0.013 (0.0085)	−0.014*** (0.0040)	−0.018*** (0.0038)
$\mathbb{I}(EE \text{ \& switcher})$	−0.018** (0.0085)	−0.012 (0.0085)	−0.016*** (0.0040)	−0.013*** (0.0039)
$\mathbb{I}(ENE \text{ \& switcher})$	−0.058*** (0.0121)	−0.054*** (0.0118)	−0.026*** (0.0051)	−0.022*** (0.0050)
$P(\pi_{nu}^{EE} = \pi_{nu}^{ENE})$	0.044	0.047	0.001	0.000
Controls for switchers	Occupation	Industry	Occupation	Industry
No. observations	318,762	318,762	375,641	375,641

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: log hourly real wage. Controls for education, union coverage, marital status, a quadratic in tenure, and a linear time trend. Robust standard errors in parenthesis, clustered by individual.

Table 4: ENE by unemployment duration, controls for occupation switchers, first differences

	≤ 9 months		≤ 8 months		≤ 7 months		≤ 6 months		≤ 5 months	
UR	-0.409*** (0.0966)	-0.408*** (0.0966)	-0.408*** (0.0966)	-0.406*** (0.0966)	-0.407*** (0.0966)	-0.406*** (0.0966)	-0.406*** (0.0966)	-0.405*** (0.0966)	-0.407*** (0.0966)	-0.406*** (0.0966)
UR $\cdot \mathbb{I}(EE)$	-1.855*** (0.6795)	-2.635*** (0.9390)	-1.853*** (0.6796)	-2.634*** (0.9389)	-1.853*** (0.6796)	-2.634*** (0.9388)	-1.852*** (0.6796)	-2.634*** (0.9388)	-1.854*** (0.6796)	-2.634*** (0.9389)
UR $\cdot \mathbb{I}(ENE)$	-0.460 (0.7499)	-0.095 (1.0840)	-0.698 (0.7546)	0.010 (1.0923)	-0.896 (0.7085)	-0.081 (1.1068)	-0.619 (0.7380)	0.148 (1.1452)	-0.673 (0.7595)	0.278 (1.1263)
UR $\cdot \mathbb{I}(LTU)$	-1.438 (1.2929)	0.252 (2.2796)	-1.078 (1.2556)	-0.539 (2.2209)	-0.600 (1.4762)	-0.121 (2.3032)	-0.970 (1.3015)	-0.710 (2.0117)	-0.709 (1.1779)	-0.585 (2.0039)
UR $\cdot \mathbb{I}(EE \text{ \& switcher})$	—	1.320 (1.3246)	—	1.321 (1.3246)	—	1.321 (1.3246)	—	1.321 (1.3246)	—	1.320 (1.3246)
UR $\cdot \mathbb{I}(ENE \text{ \& switcher})$	—	-0.622 (1.4691)	—	-1.124 (1.4812)	—	-1.306 (1.4420)	—	-1.251 (1.5029)	—	-1.492 (1.5216)
UR $\cdot \mathbb{I}(LTU \text{ \& switcher})$	—	-2.037 (2.7107)	—	-0.631 (2.6425)	—	-0.489 (2.8691)	—	-0.217 (2.5164)	—	-0.152 (2.4389)
Occ. controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
$P(\pi_{nu}^{EE} = \pi_{nu}^{ENE})$	0.163	0.076	0.250	0.065	0.324	0.078	0.214	0.060	0.243	0.046
No. observations	318,763	318,762	318,763	318,762	318,763	318,762	318,763	318,762	318,763	318,762

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: log hourly real wage. Controls for education, union coverage, marital status, a quadratic in tenure, and a linear time trend. Robust standard errors in parenthesis, clustered by individual.

Table 5: ENE by unemployment duration, controls for occupation switchers, fixed-effects

	≤ 9 months		≤ 8 months		≤ 7 months		≤ 6 months		≤ 5 months	
UR	-0.145** (0.0609)	-0.144** (0.0610)	-0.144** (0.0609)	-0.144** (0.0610)	-0.144** (0.0609)	-0.144** (0.0610)	-0.144** (0.0609)	-0.144** (0.0610)	-0.145** (0.0609)	-0.144** (0.0610)
UR · $\mathbb{I}(EE)$	-1.971*** (0.5027)	-2.603*** (0.6130)	-1.971*** (0.5027)	-2.603*** (0.6130)	-1.971*** (0.5027)	-2.603*** (0.6130)	-1.971*** (0.5027)	-2.603*** (0.6130)	-1.971*** (0.5027)	-2.603*** (0.6130)
UR · $\mathbb{I}(ENE)$	-0.246 (0.5816)	0.977 (0.8009)	-0.333 (0.5882)	0.918 (0.8073)	-0.387 (0.6040)	0.974 (0.8180)	-0.387 (0.6245)	1.101 (0.8376)	-0.173 (0.6485)	1.136 (0.8996)
UR · $\mathbb{I}(LTU)$	-0.162 (1.3940)	-0.965 (1.6313)	0.223 (1.3146)	-0.833 (1.5370)	0.377 (1.2084)	-1.321 (1.4238)	0.298 (1.0684)	-1.424 (1.3813)	-0.448 (0.9661)	-0.663 (1.1306)
UR · $\mathbb{I}(EE \text{ \& switcher})$	—	1.097 (0.7262)	—	1.097 (0.7262)	—	1.097 (0.7262)	—	1.097 (0.7262)	—	1.097 (0.7262)
UR · $\mathbb{I}(ENE \text{ \& switcher})$	—	-2.281** (0.9828)	—	-2.358** (0.9957)	—	-2.619*** (1.0072)	—	-2.869*** (1.0363)	—	-2.449** (1.0822)
UR · $\mathbb{I}(LTU \text{ \& switcher})$	—	1.041 (2.1212)	—	1.324 (1.9710)	—	2.186 (1.7984)	—	2.324 (1.6894)	—	0.136 (1.4985)
Occ. controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
$P(\pi_{nu}^{EE} = \pi_{nu}^{ENE})$	0.022	0.000	0.031	0.000	0.040	0.000	0.045	0.000	0.026	0.000
No. observations	375,642	375,641	375,642	375,641	375,642	375,641	375,642	375,641	375,642	375,641

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: log hourly real wage. Controls for education, union coverage, marital status, a quadratic in tenure, and a linear time trend. Robust standard errors in parenthesis, clustered by individual.

Table 6: Externally calibrated parameters

Parameter values		
Discount factor	β	$0.997 = 0.99^{1/3}$
Capital depreciation rate	δ	$0.008 = 0.025/3$
Production function parameter	ζ	0.33
Technology autoregressive parameter	ρ_z	$0.983 = 0.95^{1/3}$
Technology standard deviation	σ_z	0.007
Elasticity of matches to searchers	σ	0.4
Bargaining power parameter	η	0.5
Matching function constant	σ_m	1.0
Renegotiation frequency	λ	11/12 (4 quarters)

Table 7: Jointly calibrated parameters

Parameter	Description	Value	Target
ϕ	Inverse productivity premium	0.78	Average E-E wage increase (4.5%)
ξ	Prob. of good match	0.30	Average wage-improv. flow share ($\tilde{\delta}_{BG} = 0.52$)
η_ς	Search cost elasticity	1.14	Cyclicalitly of wage-improv. flow share ($\eta_{BG} = -1.35$)
κ	Hiring cost parameter	71.83	U-E probability (0.42)
$1 - \nu$	Separation probability	0.025	E-U probability (0.025)
ς_0	Scale parameter of search cost	2.15	E-E probability (0.025)
u_B	Flow value of unemployment	2.59	Relative value, non-work (0.71)

Table 8: Aggregate statistics

	y	w	$n + b$	u	v
U.S. Economy, 1964:1-2013:02					
Relative St. Dev.	1.00	0.48	0.64	5.74	6.38
Autocorrelation	0.88	0.87	0.94	0.92	0.92
Correlation with y	1.00	0.57	0.79	-0.87	0.91
Model Economy, $\lambda = 11/12$ (4 quarters)					
Relative St. Dev.	1.00	0.47	0.27	4.56	9.32
Autocorrelation	0.83	0.95	0.84	0.84	0.77
Correlation with y	1.00	0.65	0.92	-0.92	0.91
Model Economy, $\lambda = \infty$ (Flex wages)					
Relative St. Dev.	1.00	0.83	0.08	1.38	3.60
Autocorrelation	0.81	0.81	0.89	0.89	0.81
Correlation with y	1.00	1.00	0.88	-0.88	1.00

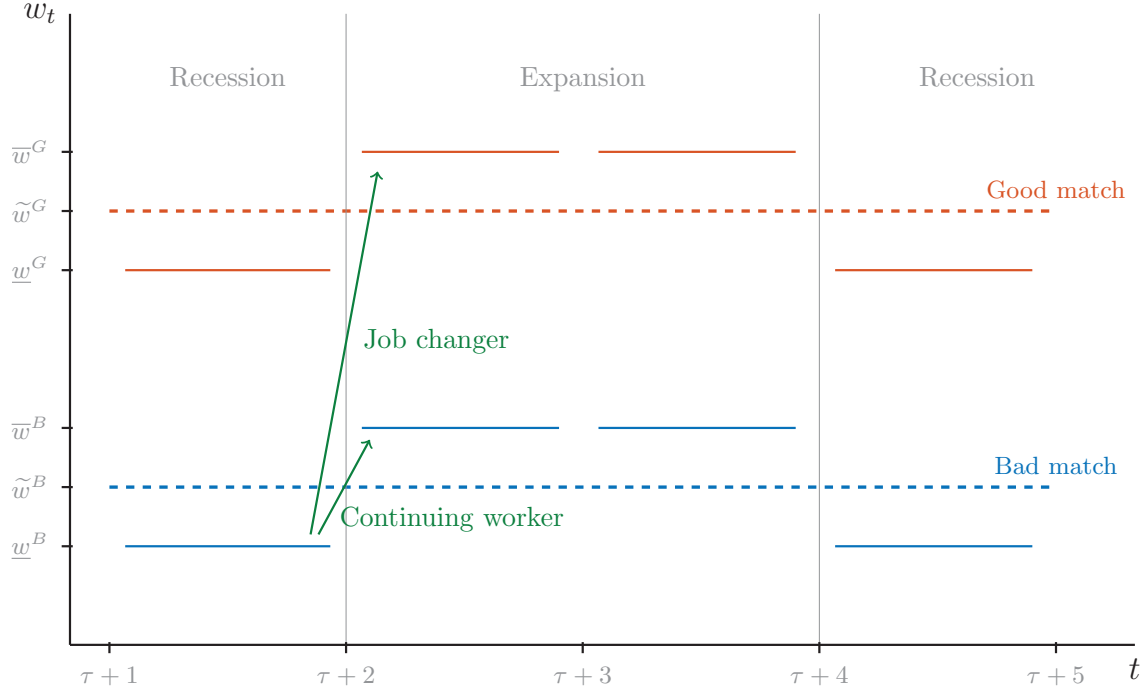
Table 9: Wage semi-elasticities: All new hires

Semi-elasticities of wages w/r.t. unemployment						
	First differences			Fixed-effects		
	SIPP	Model, 4Q	Model, flex	SIPP	Model, 4Q	Model, flex
UR	−0.46 (0.097)	−0.51	−6.83	−0.147 (0.061)	−0.88	−8.80
UR · $\mathbb{I}(\text{new})$	−1.13 (0.461)	−1.08	−4.05	−1.64 (0.326)	−0.85	−0.85

Table 10: Wage semi-elasticities: EE vs. ENE

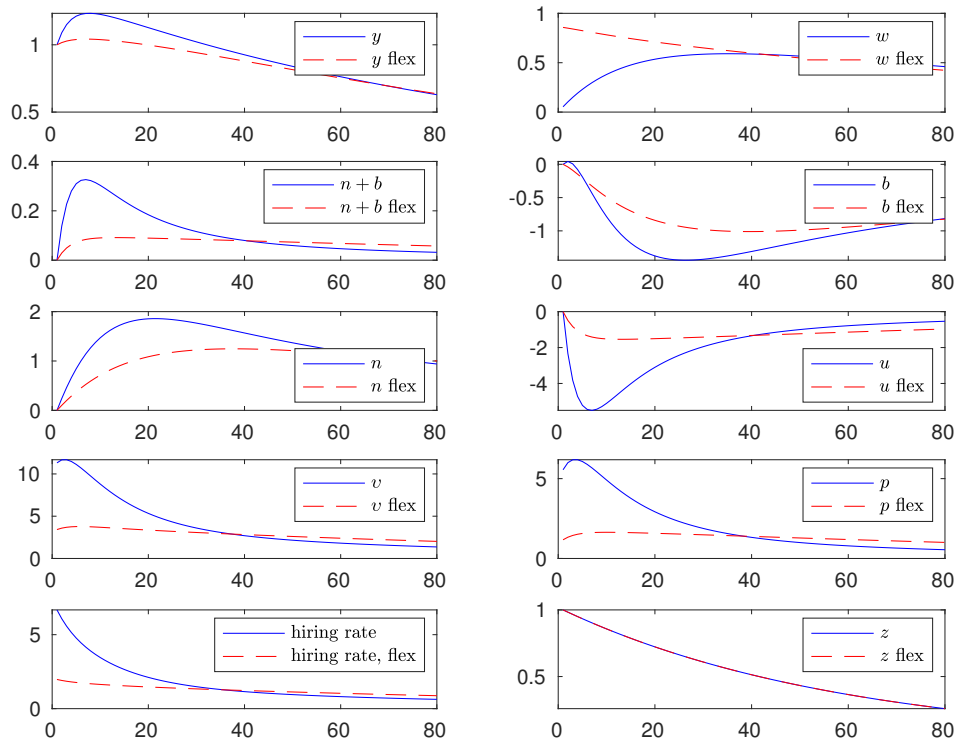
Semi-elasticities of wages w/r.t. unemployment						
	First differences			Fixed-effects		
	SIPP	Model, 4Q	Model, flex	SIPP	Model, 4Q	Model, flex
UR	−0.43 (0.097)	−0.51	−6.83	−0.145 (0.061)	−0.88	−8.80
UR · $\mathbb{I}(EE)$	−1.87 (0.680)	−1.86	−6.91	−1.97 (0.503)	−1.11	−1.53
UR · $\mathbb{I}(ENE)$	−0.44 (0.664)	−0.46	−2.03	−0.33 (0.540)	−0.32	0.08

Figure 1: New hires from employment and cyclical composition bias



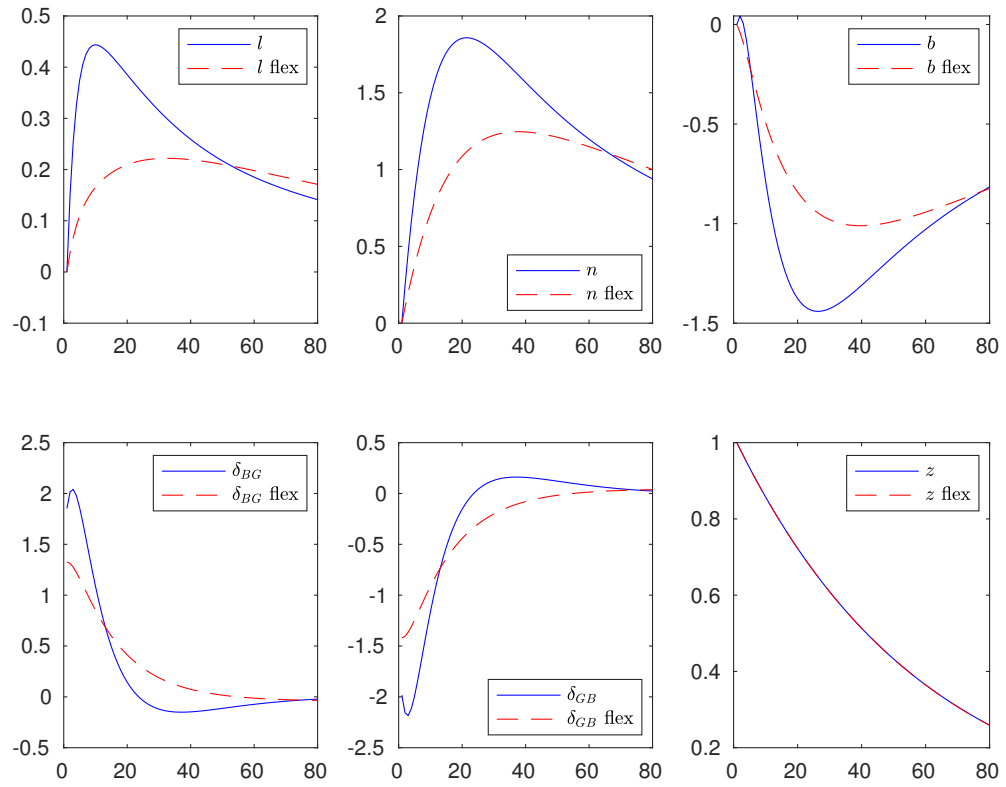
The dashed lines refer to the average wage at either a good match, \tilde{w}^G , or a bad match, \tilde{w}^B . The solid lines refer to the wage in recessions and expansions at either a good match (\underline{w}^G and \bar{w}^G) or a bad match (\underline{w}^B and \bar{w}^B).

Figure 2: Impulse responses to productivity shock



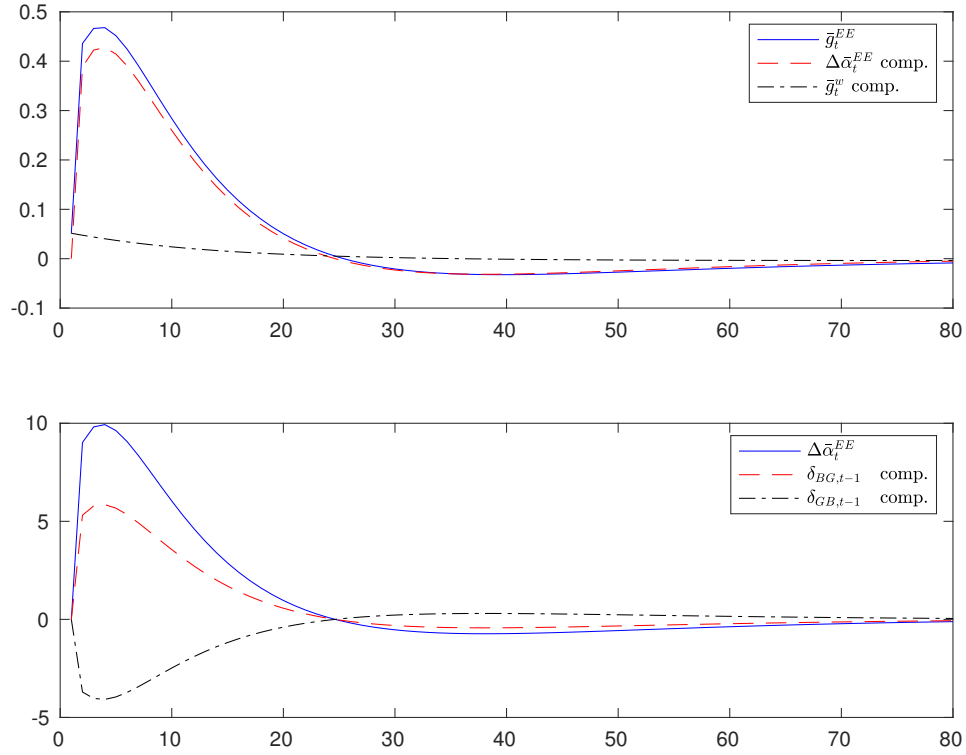
Response of aggregate quantities to one percent shock to total factor productivity.

Figure 3: Labor market composition and job flows



Response of employment and job flows to one percent shock to total factor productivity.

Figure 4: Wage growth and components



Wage growth of job-changers in response to one percent shock to total factor productivity. Top panel shows response of wage growth \bar{g}_t^{EE} as sum of a component reflecting the average change in match quality of workers making EE job transitions, $\Delta\bar{\alpha}_t^{EE}$, and a component reflecting average contract wage growth common to all workers, \bar{g}_t^w . Bottom panel shows contribution of bad-to-good and good-to-bad job flows, $\delta_{BG,t-1}$ and $\delta_{GB,t-1}$, towards changes in average match quality of job-changers, $\Delta\bar{\alpha}_t^{EE}$.