

# 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 variable 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.<sup>1</sup> 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.<sup>2</sup>

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

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<sup>1</sup> 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).

<sup>2</sup> 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 cyclicality of job changers overstate true wage flexibility. By contrast, under a standard assumption in the literature about the quality distribution of job openings, upgrading of match quality is acyclical for workers coming from unemployment. Further, as we discuss, the baseline assumption of no cyclical upgrading for these types of workers is consistent with a reasonable reading of the evidence. It follows that the wage cyclicality 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 dataset from the Survey of Income and Program Participation (SIPP) that allows us to separately estimate the wage cyclicality 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 cyclicality for new hires coming from unemployment, but substantial evidence of this phenomenon for workers making job-to-job transitions. To support the interpretation that the latter reflects mainly cyclical match improvement, we show that movement of job changers to better matches (measured by wage gains) is procyclical. 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.

To make clear how one can reconcile the panel evidence on new hire wage cyclicality with the aggregate evidence on employment volatility, 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. In particular, while the wages of new hires are sticky within the model, cyclical improvements in match quality generate new hire wage cyclicality, 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 aligned 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 noted, 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 cyclicality allowing for a job-person fixed effect on wages. The advantage of the current approach is that the wage cyclicality of new hires from unemployment provides a directly observable composition free measure of new hire wage flexibility.<sup>3</sup> 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 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 cyclicality 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). Using different methods, the estimates in these papers also suggest that new hire wage cyclicality is roughly the same as that for continuing workers. However, overall real wage variation in Portugal data exhibits much greater procyclicality than in the U.S., suggesting some limits to the relevance of this evidence to U.S. labor market volatility.<sup>4</sup>

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<sup>3</sup> 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.

<sup>4</sup> We suspect a key reason for the difference is that real wage variation in Portugal depends heavily on exchange rate dynamics while the same is not true for the U.S.

In terms of empirical methodology, our paper is closest to Haefke, Sonntag and van Rens (2013) who examine directly the wage cyclicality of new hires from unemployment. 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 begin with a discussion of the marginal cost of labor, specifically Kudlyak’s (2014) notion of the user cost of labor, and how composition bias can affect this measure. We then describe the data and the econometric methodology we use to identify a composition-free estimate of the marginal cost of labor and then present the estimates. We also present new evidence on the cyclicality of job-to-job changes and the distribution of wage changes to support the interpretation that the excess cyclicality of job changers wages likely reflects composition bias. Section 3 describes the model and Section 4 presents the numerical results and also demonstrates how the model can reconcile the aggregate and panel evidence. Section 5 elaborates on several issues involving composition effects. We first show how, due composition effects, our model can replicate Kudlyak’s evidence on the user cost of labor. We similarly show that due to composition effects our model is consistent with Beaudry and DiNardo’s evidence on the effects of starting unemployment on wage cyclicality. Finally, we discuss how the evidence in the literature is consistent with our baseline assumption of no composition effects for new hires coming from unemployment. Concluding remarks are in Section 5.

## 2 Data and Empirics

In this section we present evidence to suggest that after controlling for composition effects, the wages of new hires are no more flexible than those for new hires. We then use the evidence to draw implications about the cyclicality of the marginal cost of labor. We first discuss how to measure the marginal cost of labor and how composition effects can distort this measure. We then discuss our identification scheme for isolating composition

effects, which relies on distinguishing new hires who change jobs from those coming from unemployment. We then describe the data and present the estimation results.

## 2.1 The Cyclicity of 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. The user cost is the sum of two components. The first component is the current new hire wage. The second is 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  $t + 1$ . This second term takes into account that the future wage contracts may depend on economic conditions at the time the worker is hired. Accordingly, let  $w_{t,t+s}$  be the wage paid at  $t + s$  to a worker hired in  $t$ ,  $\rho$  the worker survival rate, and  $\beta$  the discount factor. Then, the user cost is given by

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

The second component of the user cost  $f_t$  summarizes the net present value gain in compensation to a worker who is hired at  $t$  relative to being hired at  $t + 1$ .

The second component  $f_t$  is only non-zero if the future stream of wages paid to the worker is permanently indexed to the state of the economy at the time she is hired. This will be true in an environment such as Pissarides (2009), where wages are flexibly negotiated at the start but then smoothed over the duration of the employment relation. Such a framework implies not only that new hires wages are more cyclical than those of continuing workers, but also that the user cost is more cyclical than both.

Absent such history dependence, however, the term  $f_t$  will equal zero. This is the case for both period-by-period Nash bargaining and staggered Nash bargaining, which will serve as the core of the model we develop later.<sup>5</sup> Under both of these wage protocols, workers receive “equal treatment” within the firm. That is, workers with the same fundamental characteristics (productivity and outside option) receive the same wage. After controlling for these fundamentals, the time of hire does not affect the wage and  $f_t$  is thus zero. For example, with staggered Nash bargaining, new hires receive the same wage as existing

<sup>5</sup> Under staggered Nash bargaining, the wage received by a worker is independent of when the worker is hired, conditional on the prevailing wage within a firm. Key to this is the assumption that workers hired in-between contracting period receive the prevailing firm wage.

workers with the same fundamentals. In this case the wages of either can be used for estimating the cyclical of the user cost.<sup>6</sup>

Hence, to test for contractual flexibility in wages à la Pissarides, one can attempt to directly measure the cyclical of the user cost of labor and compare that to the hiring wage, as in Kudlyak (2014) or Basu and House (2017); or simply test whether new hire wages are more cyclical than those of existing workers, as in Bilts (1985). But for either procedure to be valid, the wage must be expressed in efficiency units of labor. Failure to do so will overstate both the wage cyclical of new hires relative to existing workers and the cyclical of the user cost. In particular, if workers are hired into more productive matches at a higher rate in booms than in recessions, the cyclical of hiring wages and the user cost will reflect not only contractual wage flexibility, but also cyclical changes in the distribution of efficiency units of labor across workers.

As we noted earlier, our approach to testing for the wage flexibility of new hires relative to existing workers that controls for cyclical composition rests on the distinction between new hires from unemployment and those coming from other jobs. Under the assumption that the cyclical selection of workers into jobs of various quality works predominantly through employed workers searching on-the-job, we argue that the wage cyclical of new hires from non-employment serves as a valid measure of the cyclical of the composition-adjusted hiring wage. As we discuss later, our argument is reasonable to the extent that the quality distribution of available jobs is invariant to the aggregate state. We also show in Section 5.3 that our baseline assumption is reasonable in light of existing evidence.<sup>7</sup>

We use monthly data to classify new hires as job-changers or new hires from non-employment, and we then estimate separate wage elasticities for both groups. Under our baseline assumption, the cyclical composition effect will be concentrated on the wages of job-changers, while the wage cyclical of new hires from unemployment provides a composition-free measure of cyclical wage flexibility. Hence, we can use our estimates to test whether the composition-free new hire wage displays more cyclical flexibility than wages of continuing workers. We find no evidence that the wages of new hires are more flexible than those of existing workers. Our findings are thus inconsistent with models of history dependence and consistent with models of Nash bargaining where the wages of new hires are tied to the wages of existing workers. As a direct implication, the cyclical of the user

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<sup>6</sup> Of course, while the wages of incumbent and new hires are equally cyclical under both bargaining protocols, the common absolute cyclicalities are lower under staggered Nash bargaining than under period-by-period Nash bargaining. Infrequent bargaining allows the Nash solution to generate absolute wage cyclicalities consistent with data under standard calibrations of the worker's bargaining power and the value of leisure.

<sup>7</sup> 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. We explore the robustness of this assumption in Section 5.3.

cost of labor can be read from either the wage of continuing workers or the wage of new hires from non-employment.

In what follows, we discuss the data, our empirical framework, and the motivation and robustness for our baseline assumption.

## 2.2 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.”<sup>8</sup>

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.<sup>9</sup> As the SIPP contains multiple

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<sup>8</sup> Specifically, we find that the vast majority of earnings changes for workers employed at the same job continuously 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).

<sup>9</sup> 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.

cohorts, at each point in time the sample is always representative of the U.S. population, in contrast to other widely used panel datasets 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.<sup>10</sup>

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

### 2.3 Baseline Empirical Framework

We begin with 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).<sup>11</sup> We regress the log wage of individual  $i$  in job  $j$  at time  $t$ ,  $w_{ijt}$ , on individual level characteristics  $x_{ijt}$ , including education, job tenure, and a time trend; the unemployment rate  $u_t$ ; an indicator variable  $I(new_{ijt})$  equal to one if the worker is a new hire and zero if not; and an interaction term in  $I(new_{ijt})$  and  $u_t$ . To control for unobserved individual characteristics, we estimate a regression equation in fixed effects and in first differences. For ease of notation, we write a single measurement equation indexed by  $m$ , where  $m = FD$  corresponds to estimation by first differences and  $m = FE$  corresponds to estimation by fixed effects:

$$\Delta^m \log w_{ijt} = \Delta^m x'_{ijt} \pi_x + \pi_u \cdot \Delta^m u_t + \pi_n \cdot I(new_{ijt}) + \pi_{nu} \cdot I(new_{ijt}) \cdot \Delta^m u_t + e_{ijt} \quad (1)$$

where  $e_{ijt}$  is random error term.<sup>12</sup>

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

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<sup>10</sup> 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.

<sup>11</sup> 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, Guimarões, and Portugal (2012); Deveraux (2002); Martins, Solon, and Thomas (2012); and Hagedorn and Manovskii (2013).

<sup>12</sup> Note, 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. For example, with first differences, we could have  $\Delta^{FD} \log w_{ijt} = \log w_{ijt} - \log w_{i\ell\tau}$ , where  $\ell \neq j$  and  $\tau < t - 1$ .

unemployment rate is meant to measure the extra cyclical of new hires wages. In particular, the coefficient  $\pi_u$  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.<sup>13</sup>

At this point we make two observations: First, with exception of Haefke *et al.* (2013), the prevailing literature typically does not distinguish between new hires coming from unemployment and those coming from other jobs.<sup>14</sup> Second, since changes in wages of workers making job-to-job transitions include variation in quality across jobs, cyclical movements in job match quality will bias the new hire effect for workers coming from employment. We turn to these issues shortly.

The regressions are based on triannual data, i.e. data at a four month frequency.<sup>15</sup> For comparability to Bils (1985), we only use observations for men between the ages of 20 and 60. Accordingly, unemployment is the prime age 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.<sup>16</sup> The Appendix provides additional information on variable construction, including the individual level characteristics we use. Finally, we compute robust standard errors, clustered by individual.

Table 1 presents the results. Our results are consistent with the key findings of the literature:  $\pi_{nu}$  is statistically significant and negative (along with  $\pi_u$ ), suggesting greater cyclical sensitivity of new hires’ wages. The first column presents the estimates of equation (1) using fixed effects and the second presents estimates using first differences. The results are robust across specifications. Similar to Bils (1985), we find that new hires’ wages are

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<sup>13</sup> The 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.

<sup>14</sup> 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.

<sup>15</sup> 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.

<sup>16</sup> 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.

significantly more cyclical than those for existing workers. When estimating the equation in first differences, the semi-elasticity of new hire wages is  $-1.583$ , compared to  $-0.461$  for continuing workers. With fixed effects, the new hire semi-elasticity is estimated to be  $-1.790$ , 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 a semi-elasticity of 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](#).

## 2.4 Reconsidering the New Hire Effect

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 to this view, the present value of wages is highly cyclical 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  $\pi_{nu}$  reflects that the new hires receive a persistently higher wage contract when hired during a boom; and the smaller estimate for  $\pi_u$  reflects that wages are insulated from aggregate conditions for the rest of the match. [Kudlyak \(2014\)](#) offers a similar interpretation, where excess cyclicity in the user cost of labor goes hand in hand with cyclical wages of new hires relative to continuing workers.

We offer an alternative interpretation of the results in [Table 1](#). While new hire wage cyclicity might be indicative of contractual wage flexibility, such a conclusion cannot be drawn without also considering the possibility of “cyclical composition effects”, whereby workers move to better jobs at a higher rate during booms. To the extent that workers are more likely to move to better jobs during an expansion, the regression equation (1) will generate evidence of greater wage cyclicity for newly hired workers.

[Figure 1](#) illustrates how procyclical match upgrading may bias estimates of new hire wage cyclicity. 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: a modest cyclical increase in wages common to both job changers and continuing workers and 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 hiring costs of a firm; however, an econometrician who does not take into account the cyclical change in match quality may conclude otherwise.

Specifically, suppose that the error term  $e_{ijt}$  in the regression equation (1) takes the form

$$e_{ijt} = \Delta^m q_{ij} + \varepsilon_{ijt} \quad (2)$$

where  $\Delta^m q_{ij}$  represents the change in unobserved match quality at job  $j$ . If workers are more likely to find better matches when the unemployment rate is low – or similarly, if the share of workers moving from bad to good matches of total job flows is procyclical – then the composite error term  $e_{ijt}$  will be correlated with  $\Delta^m u_t$ , the change in unemployment:

$$Cov(\Delta^m q_{ij}, \Delta^m u_t) < 0. \quad (3)$$

As a consequence, the estimated coefficient intended to identify the excess cyclicity of new hires wages,  $\pi_{nu}$ , will be biased downward. Hence, estimates of a negative  $\pi_{nu}$  would reflect cyclical composition bias rather than greater flexibility of new hire wages.

How then do we disentangle the relative contribution of cyclical composition and contractual wage cyclicity to estimates of excess wage cyclicity of new hires? We start under the baseline assumption that the quality of jobs available to a given individual are largely invariant to the aggregate state. Under this baseline, the set of jobs accepted by a worker from unemployment will not vary with the aggregate state, and the wages of workers hired from unemployment will be free of cyclical selection. In contrast, workers from employment will typically only accept a job if it offers a higher job value than that associated with their current match.<sup>17</sup> Because employed workers can more easily sample the set of possible jobs during an expansion, the incentive to upgrade their match will be procyclical. As a result, employed workers looking to upgrade will raise search efforts in booms, implying more cyclical average wage gain for job changers than for new hires from non-employment. Hence, the acceptance rule of workers searching on-the-job and the cyclical variability in contact rates generate cyclical composition bias for workers searching on the job. 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

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<sup>17</sup> We qualify this statement, as a non-negligible fraction of workers searching on-the-job move to lower-wage matches, presumably for non-economic reasons; and this fraction decreases during an expansion.

literature arguing that is easier for workers in employment to locate better matches during expansions than recessions (Barlevy, 2002).

If the estimates of new hire wage cyclicality from Table 1 reflect cyclical composition but not contractual wage flexibility, the negative coefficient  $\pi_{nu}$  is identified from cyclical wages of job-changers. To test this proposition, we estimate a variant of equation (1) that allows us to isolate the wage cyclicality of new hires from employment versus non-employment:

$$\begin{aligned} \Delta^m \log w_{ijt} = & \Delta^m x'_{ijt} \pi_x + \pi_u \cdot \Delta^m u_t + \pi_n^{ENE} \cdot I(ENE_{ijt}) + \pi_n^{EE} \cdot I(EE_{ijt}) \\ & + \pi_{nu}^{ENE} \cdot I(ENE_{ijt}) \cdot \Delta^m u_t + \pi_{nu}^{EE} \cdot I(EE_{ijt}) \cdot \Delta^m u_t + e_{ijt}, \end{aligned} \quad (4)$$

where “*ENE*” signifies a new hire with an intervening spell of non-employment and “*EE*” signifies a new hire who makes direct job-to-job transitions.<sup>18</sup> Under our assumption,  $\pi_{nu}^{EE} < 0$  and  $\pi_{nu}^{ENE} = 0$  will indicate a new hire effect that is driven by cyclical composition rather than contractual wage flexibility.<sup>19</sup>

Table 2 presents the results for fixed-effects and first differences estimators. 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  $\pi_{nu}^{ENE}$  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. Indeed, the coefficient  $\pi_{nu}^{EE}$  on the job-changer interaction term is higher than the coefficient  $\pi_{nu}$  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 by at least the

<sup>18</sup> Note that workers making *ENE* transitions may have gone a full wave without employment. We drop this observation, as the worker is not employed and earns zero wages.

<sup>19</sup> 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; and (3) we have a more representative and longer sample. In addition, they are unable to control for occupation, which we show in the Appendix can be important for eliminating a spurious new hire effect.

5% level.<sup>20</sup>

## 2.5 The distribution of wage changes and cyclical of job-to-job flows

Next, we present several facts to support the idea that the excess cyclical of job-changers wages reflect composition effects. The first set involves the distribution of wages for workers making job-to-job changes. The second involves the cyclical of job-to-job flows.

We first note that job-changers move not only to improve their respective matches but also for idiosyncratic reasons such as family reasons or the imminent termination of the previous job (see Tjaden and Wellschmied, 2014). While the average wage changes of job-changers is modest – plus 4.5%, from the third column of Table 2 – the conditional wage changes are considerably larger in magnitude, equal to plus 30% for workers realizing wage gains and minus 23% for workers realizing wage losses. Hence, movements up and down the job-ladder involve large gains and losses. 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  $-0.247$ , 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 around zero, with an average log wage residual of  $0.057$ . This is consistent with the often idiosyncratic reasons for job changes described earlier, where a job transfer is motivated by reasons unrelated to pay.

Finally, we show that the share of job-changers moving to jobs with better pay is procyclical. We first create an indicator variable,  $I(+)_ijt$ , 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:

$$I(+)_ijt = \alpha + \Delta x'_{ijt} \beta_x + \beta_u \cdot u_t + \varepsilon_{ijt}$$

The coefficient  $\beta_u$  tells us how the share of workers that improve match quality varies with the unemployment rate. Our point estimate of  $\beta_u$  is  $-1.40$ , significant at the one percent

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<sup>20</sup> The interpretation of our coefficient estimates is sensitive to the assumption that there is no cyclical selection of workers from unemployment into jobs of various qualities. In a separate sub-section in Section 5, we further discuss the robustness of our identifying assumption. Moreover, in the Appendix, we employ a weaker criterion for identification, that there is no *unobserved* cyclical selection of unemployed workers into employment. Our results are robust to these controls.

level, and the implied bad-to-good flows are plotted against the unemployment rate in Figure 2. The estimate suggests that if the unemployment rate increases by one percentage point, the share of workers that are upgrading their jobs drops by 0.014 percentage points.<sup>21</sup> This evidence is consistent with the narrative that workers from employment looking for higher-paying jobs concentrate their search during periods where it is easier to find a new match.

Thus far, we have interpreted our empirical findings through the identifying assumption that cyclical selection is concentrated on workers making job-to-job changes. In the next section, we check whether this assumption and our interpretation of the regression estimates is quantitatively consistent with the data. We develop a model of equilibrium unemployment with on-the-job search, variable match quality, and wage stickiness for new hires. We find that the model is successfully able to simultaneously match the untargeted micro and macro moments. Crucially, in our model, new hires wages are no more flexible than those for existing workers; yet data generated from the model will give rise to the appearance of new hire wage flexibility when evaluated by the typical regression from the literature.

### 3 Model

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

#### 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  $\phi$  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:

$$l_t = n_t + \phi b_t. \tag{5}$$

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<sup>21</sup> Later, we use this estimate to discipline our quantitative model.

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  $\xi$  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

$$\bar{u}_t = 1 - \bar{n}_t - \bar{b}_t. \quad (6)$$

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  $\nu$ , 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.<sup>22</sup> 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  $\varsigma_{bt}$ . 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.<sup>23</sup> We assume that these workers search with fixed intensity  $\varsigma_n$  and accept good or bad matches. This is equivalent to a reallocation shock whereby workers in good matches

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<sup>22</sup> Strictly 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.

<sup>23</sup> For 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).

are forced to search on-the-job with probability  $\varsigma_n$ . 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.<sup>24</sup> Not only are job-to-job changes with a reduction in wages an empirical regularity, but their level and cyclical nature is key for understanding the wage cyclicality of job changers via composition effects, as we show later.

We derive the total efficiency units of search effort  $\bar{s}_t$  as a weighted sum of search intensity across the two types:

$$\bar{s}_t = \bar{u}_t + \nu(\varsigma_{bt}\bar{b}_t + \varsigma_n\bar{n}_t). \quad (7)$$

The first term reflects search intensity of the unemployed; the second term, the search intensity of the employed. 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:

$$\bar{m}_t = \sigma_m \bar{s}_t^\sigma \bar{v}_t^{1-\sigma}, \quad (8)$$

where  $\sigma$  is the elasticity of matches to units of search effort and  $\sigma_m$  reflects the efficiency of the matching process.

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

$$p_t = \frac{\bar{m}_t}{\bar{s}_t}. \quad (9)$$

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

$$p_t^n = \xi p_t, \quad (10)$$

$$p_t^b = (1 - \xi)p_t. \quad (11)$$

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

$$q_t^m = \frac{\bar{m}_t}{\bar{v}_t}. \quad (12)$$

Not all matches lead to hires, however, and hires vary by quality. The probability  $q_t^n$  a

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<sup>24</sup> For 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.

vacancy leads to a good quality hire and the probability  $q_t^b$  it leads to a bad quality one are given by

$$q_t^n = \xi q_t^m, \quad (13)$$

$$q_t^b = (1 - \xi) \left( 1 - \frac{\nu \varsigma_{bt} \bar{b}_t}{\bar{s}_t} \right) q_t^m. \quad (14)$$

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,  $\xi$ , 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

$$q_t = q_t^n + \phi q_t^b. \quad (15)$$

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

## 3.2 Firms

Firms produce output  $y_t$  using capital and labor according to a Cobb-Douglas production technology:

$$y_t = z_t k_t^\alpha l_t^{1-\alpha}, \quad (16)$$

where  $k_t$  is capital and  $l_t$  labor in efficiency units. Capital is perfectly mobile. Firms rent capital on a period by period basis. They add labor through a search and matching process that we describe shortly. The current value of  $l_t$  is a predetermined state.

Labor in efficiency units is the quality adjusted sum of good and bad matches in the firm (see equation (5)). 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 follow 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 labor quality mix  $\gamma_t$  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  $\rho_t^i$  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:

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

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

where  $q_t^i v_t$  is the quantity of type  $i$  matches and where equations (13) and (14) define  $q_t^n$  and  $q_t^b$ . The probability of retaining a worker, in turn, is the product of the job survival probability  $\nu$  and the probability the worker does not leave for a job elsewhere, giving the following expressions for good and bad matches:

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

$$\rho_t^b = \nu(1 - \varsigma_b p_t^n), \quad (21)$$

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,  $\rho_t$ , as the following convex combination of  $\rho_t^n$  and  $\rho_t^b$ :

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

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

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

where the expected number of efficiency weighted new hires per vacancy  $q_t$  is given by equation (15). The evolution of  $l_t$  is then given by:

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

It is useful to define  $\bar{\gamma}_t^m \equiv (q_t^b v_t) / (q_t^n v_t) = q_t^b / q_t^n$  as the ratio of newly-formed bad to good matches. Then, making use of equations (15), (17), (18), (19) and (23) to characterize how the quality mix of workers  $\gamma_t = b_t / n_t$  evolves over time, we obtain:

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

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

We now turn to the firm's decision problem. Assume that labor recruiting costs are quadratic in the hiring rate for labor in efficiency units,  $x_t$ , and homogeneous in the existing stock  $l_t$ .<sup>25</sup> Then let  $\Lambda_{t,t+1}$  be the firm's stochastic discount factor (i.e., the household's intertemporal marginal rate of substitution),  $r_t$  be the rental rate of capital, and  $w_t$  be the wage per efficiency unit of labor. Then the firm's decision problem is to choose capital  $k_t$  and the hiring rate  $x_t$  to maximize 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 quality mix of labor  $\gamma_t$ , and given the expected paths of rents and wages. We express the value of each firm  $F_t(l_t, \gamma_t, w_t) \equiv F_t$  as

$$F_t = \max_{k_t, x_t} \left\{ z_t k_t^\alpha l_t^{1-\alpha} - \frac{\kappa}{2} x_t^2 l_t - w_t l_t - r_t k_t + E_t \{ \Lambda_{t,t+1} F_{t+1} \} \right\},$$

subject to equations (24) and (25), and given the values of the firm level states  $(l_t, \gamma_t, w_t)$  and the aggregate state vector.<sup>26</sup> 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.

Given constant returns and perfectly mobile capital, the firm's value  $F_t$  is homogeneous in  $l_t$ . The net effect is that each firm's choice of the capital/labor ratio and the hiring rate is independent of its size. Let  $J_t$  be firm value per efficiency unit of labor and let  $\check{k}_t \equiv k_t/l_t$  be its capital labor ratio. Then

$$F_t = J_t \cdot l_t, \tag{26}$$

with  $J_t \equiv J_t(\gamma_t, w_t)$  given by

$$J_t = \max_{\check{k}_t, x_t} \left\{ z_t \check{k}_t^\alpha - \frac{\kappa}{2} x_t^2 - w_t - r_t \check{k}_t + (\rho_t + x_t) E_t \{ \Lambda_{t,t+1} J_{t+1} \} \right\}, \tag{27}$$

subject to (24) and (25).

The first order condition for capital rental is

$$r_t = \alpha z_t \check{k}_t^{\alpha-1}. \tag{28}$$

Given Cobb-Douglas production technology and perfect mobility of capital,  $\check{k}_t$  does not vary across firms.

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<sup>25</sup> We assume quadratic recruiting costs because we have temporary wage dispersion due to staggered contracts and perfectly mobile capital. With proportional costs, all capital would flow to the low wage firms.

<sup>26</sup> The 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.

The first order condition for hiring is

$$\kappa x_t = E_t \left\{ \Lambda_{t,t+1} \left[ J_{t+1} + (\rho_t + x_t) \left[ \frac{\partial J_{t+1}}{\partial \gamma_{t+1}} + \frac{\partial J_{t+1}}{\partial w_{t+1}} \frac{\partial w_{t+1}}{\partial \gamma_{t+1}} \right] \frac{\partial \gamma_{t+1}}{\partial x_t} \right] \right\}. \quad (29)$$

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 (29) 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.<sup>27</sup>

### 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

$$U_t = u_B + E_t \left\{ \Lambda_{t,t+1} \left[ p_t^n \bar{V}_{t+1}^n + p_t^b \bar{V}_{t+1}^b + (1 - p_t) U_{t+1} \right] \right\}, \quad (30)$$

where  $p_t^n = \xi p_t$ ,  $p_t^b = (1 - \xi)p_t$ ,  $p_t$  is given by (9), and where  $\bar{V}_{t+1}^n$  and  $\bar{V}_{t+1}^b$  are the average values of good and bad matches at time  $t + 1$ .<sup>28</sup>

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

$$c(s_{it}) = \frac{s_0}{1 + \eta_\zeta} s_{it}^{1 + \eta_\zeta}$$

<sup>27</sup> Under our calibration, the effect will be zero, up to a first order. See the Appendix for details.

<sup>28</sup> Technically, 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  $\bar{V}_{x,t+1}^i = \int V_{t+1}^i(\gamma, w) (x_t(\gamma, w) / \bar{x}_t) dG_t(\gamma, w)$ , where  $\bar{x}_t = \int x_t(\gamma, w) dG_t(\gamma, w)$ . Since  $w$ ,  $\gamma$  and  $x$  in the steady state are identical across firms,  $\bar{V}_{x,t+1}^i = \bar{V}_{t+1}^i$  up to a first order.

where  $i = b, n$ . As we discussed earlier, workers in bad matches search on the job with variable intensity  $\varsigma_{bt}$  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  $\varsigma_n$ .<sup>29</sup>

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

$$V_t^b = \max_{\varsigma_{bt}} \left\{ w_{bt} - \nu c(\varsigma_{bt}) + E_t \left\{ \Lambda_{t,t+1} \left[ \nu(1 - \varsigma_{bt} p_t^n) V_{t+1}^b + \nu \varsigma_{bt} p_t^n \bar{V}_{t+1}^n + (1 - \nu) U_{t+1} \right] \right\} \right\} \quad (31)$$

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  $\nu$ , he searches with variable intensity  $\varsigma_{bt}$ . 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.

A worker in the bad match chooses the optimal search intensity  $\varsigma_{bt}$  according to (31), satisfying

$$\varsigma_0 \varsigma_{bt}^{\eta_\varsigma} = E_t \left\{ \Lambda_{t,t+1} p_t^n \left( \bar{V}_{t+1}^n - V_{t+1}^b \right) \right\} \quad (32)$$

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 (32) how the model can generate procyclical search 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.

$$V_t^n = w_{nt} - \nu c(\varsigma_n) + E_t \left\{ \Lambda_{t,t+1} \left[ \nu(1 - \varsigma_n p_t) V_{t+1}^n + \nu \varsigma_n \left( p_t^n \bar{V}_{t+1}^n + p_t^b \bar{V}_{t+1}^b \right) + (1 - \nu) U_{t+1} \right] \right\} \quad (33)$$

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

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<sup>29</sup> In 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 19, 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.

(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.<sup>30</sup>

### 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  $\phi$  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  $\phi w_t$  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. It 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.

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  $J_t$ , derived in Section 3.2 (equation (27)). For good workers, the relevant surplus is the difference between the value of a good match and unemployment:

$$H_t = V_t^n - U_t \tag{34}$$

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  $1/(1 - \lambda)$ .<sup>31</sup> 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

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<sup>30</sup> 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 cyclical nature 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.

<sup>31</sup> 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.

in the current period.<sup>32</sup> 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

$$H_t^\eta J_t^{1-\eta} \tag{35}$$

subject to

$$w_{t+1} = \begin{cases} w_t & \text{with probability } \lambda \\ w_{t+1}^* & \text{with probability } 1 - \lambda \end{cases} \tag{36}$$

where  $w_{t+1}^*$  is the wage chosen in the next period if the parties are able to re-bargain and where  $\eta$  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  $J_t \equiv J_t(\gamma_t, w_t)$ ). Then the first order condition for  $w_t^*$  is given by

$$\chi_t^* J_t^* = (1 - \chi_t^*) H_t^* \tag{37}$$

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 (37) is a variation of the conventional sharing rule, where the relative weight  $\chi_t$  depends not only on the worker's bargaining power  $\eta$ , but also on the differential firm/worker horizon, reflected by the term  $\mu_t/\epsilon_t$  as discussed in GT.<sup>33</sup> While the horizon effect is interesting from a theoretical perspective, GT shows that it is quantitatively miniscule, implying  $\chi_t$  is very close to  $\eta$ .

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,  $\lambda^i$ .

In general, the new contract wage will be a function of the firm level state  $\gamma_t$  (the ratio of bad to good matches), as well as the aggregate state vector. However, given our assumptions that steady state retention rates are the same for good and bad matches and that wages are

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<sup>32</sup> We suppress the dependence of  $w^*$  and similar objects on the firm's composition in the notation.

<sup>33</sup> 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, 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.

proportional to productivity, the average contract wage,  $\bar{w}_t^*$ , is independent of composition in the first order approximation. Accordingly, to a first order, we can express the evolution of average wages  $\bar{w}_t$  as

$$\bar{w}_t = (1 - \lambda)\bar{w}_t^* + \lambda\bar{w}_{t-1} \quad (38)$$

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

$$\bar{w}_t = \int_{w,\gamma} w dG_t(\gamma, w) \quad (39)$$

$$\bar{w}_t^* = \int_{w,\gamma} w_t^*(\gamma) dG_t(\gamma, w) \quad (40)$$

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 composition less than or equal to  $\gamma$ . (See the Appendix for details.)

### 3.5 Households: Consumption and Saving

We adopt the representative family construct, following Merz (1995) and Andolfatto (1996), allowing for perfect consumption insurance. There is a measure of families on the unit interval, each with a measure one of workers. Before making allocating resources to per-capita consumption and savings, the family pools all wage and unemployment income. Additionally, the family owns diversified stakes in firms that pay out profits. The household can then assign consumption  $\bar{c}_t$  to members and save in the form of capital  $\bar{k}_t$ , which is rented to firms at rate  $r_t$  and depreciates at the rate  $\delta$ .

Let  $\Omega_t$  be the value of the representative household. Then,

$$\Omega_t = \max_{\bar{c}_t, \bar{k}_{t+1}} \{ \log(\bar{c}_t) + \beta E_t \Omega_{t+1} \} \quad (41)$$

subject to

$$\begin{aligned} & \bar{c}_t + \bar{k}_{t+1} + \frac{s_0}{1 + \eta_\varsigma} \left\{ \nu \varsigma_n^{1+\eta_\varsigma} \bar{n}_t + \nu \varsigma_{bt}^{1+\eta_\varsigma} \bar{b}_t \right\} \\ & = \bar{w}_t \bar{n}_t + \phi \bar{w}_t \bar{b}_t + (1 - \bar{n}_t - \bar{b}_t) u_B + (1 - \delta + r_t) \bar{k}_t + T_t + \Pi_t, \end{aligned} \quad (42)$$

and

$$\bar{n}_{t+1} = \bar{\rho}_t^n \bar{n}_t + \xi p_t \bar{s}_t \quad (43)$$

$$\bar{b}_{t+1} = \bar{\rho}_t^b \bar{b}_t + \xi \bar{\gamma}_t^m p_t \bar{s}_t \quad (44)$$

where  $\Pi_t$  are the profits from the household's ownership holdings in firms and  $T_t$  are lump sum transfers from the government.<sup>34</sup>

The first-order condition from the household's savings problem gives

$$1 = (1 - \delta + r_t)E_t\{\Lambda_{t,t+1}\} \quad (45)$$

where  $\Lambda_{t,t+1} \equiv \beta \bar{c}_t / \bar{c}_{t+1}$ .

### 3.6 Resource Constraint, Government Policy, and Equilibrium

The resource constraint states that the total resource allocation towards consumption, investment, vacancy posting costs, and search costs is equal to aggregate output:

$$\bar{y}_t = \bar{c}_t + \bar{k}_{t+1} - (1 - \delta)\bar{k}_t \quad (46)$$

$$+ \frac{\kappa}{2} \int_i x_t^2 l_t di + \frac{s_0}{1 + \eta_\varsigma} \left( \nu \varsigma_n^{1+\eta_\varsigma} \bar{n}_t + \nu \varsigma_{bt}^{1+\eta_\varsigma} \bar{b}_t \right) \quad (47)$$

The government funds unemployment benefits through lump-sum transfers:

$$T_t + (1 - \bar{n}_t - \bar{b}_t) u_B = 0. \quad (48)$$

A recursive equilibrium is a solution for (i) a set of functions  $\{J_t, V_t^n, V_t^b, U_t\}$ ; (ii) the contract wage  $w_t^*$ ; (iii) the hiring rate  $x_t$ ; (iv) the subsequent period's wage rate  $w_{t+1}$ ; (v) the search intensity of a worker in a bad match  $\varsigma_{bt}$ ; (vi) the rental rate on capital  $r_t$ ; (vii) the average wage, the average contract wage, the average search intensity of workers in bad matches and the average hiring rate,  $\bar{w}_t$ ,  $\bar{w}_t^*$ ,  $\bar{\varsigma}_{bt}$  and  $\bar{x}_t$ ; (viii) the capital labor ratio  $\bar{k}_t$ ; (ix) the average consumption and capital,  $\bar{c}_t$  and  $\bar{k}_{t+1}$ ; (x) the average employment in good and bad matches,  $\bar{n}_t$  and  $\bar{b}_t$ ; (xi) the density function of composition and wages across workers  $dG_t(\gamma, w)$ ; and (xii) a transition function  $Q_{t,t+1}$ . The solution is such that (i)  $w_t^*$  satisfies the Nash bargaining condition (37); (ii)  $x_t$  satisfies the hiring condition (29); (iii)  $w_{t+1}$  is given by the Calvo process for wages (36); (iv)  $\varsigma_{bt}$  satisfies the first-order condition for search intensity of workers in bad matches (32); (v)  $r_t$  satisfies (28); (vi)  $\bar{w}_t = \int_{w,\gamma} w dG_t(\gamma, w)$ ,  $\bar{w}_t^* = \int_{w,\gamma} w_t^*(\gamma) dG_t(\gamma, w)$ ,  $\bar{\varsigma}_{bt} = \int_{w,\gamma} \varsigma_{bt}(\gamma, w) dG_t(\gamma, w)$  and  $\bar{x}_t = \int_{w,\gamma} x_t(\gamma, w) dG_t(\gamma, w)$ ; (vii) the rental market for capital clears,  $\bar{k}_t = \bar{k}_t / (\bar{n}_t + \phi \bar{b}_t)$ ; (viii)  $\bar{c}_t$  and  $\bar{k}_{t+1}$  solve the household problem (41); (ix)  $\bar{n}_t$  and  $\bar{b}_t$  evolve according to (43) and (44); (x) the evolution

<sup>34</sup> Chodorow-Reich and Karabarbounis (2016) show the addition of non-separable utility from leisure can greatly increase the difficulty of generating sufficient unemployment volatility when the model is calibrated to match the estimated cyclical volatility of the opportunity cost of employment. For simplicity we do not include non-separable utility from leisure, but in ongoing work we show that our model with staggered wage contracting is robust to this critique.

of  $G_t$  is consistent with  $Q_{t,t+1}$ ; (xi)  $Q_{t,t+1}$  is defined in the Appendix.

### 3.7 New Hire Wages and Job-to-Job Flows

Here we describe how our model is able to capture the panel data evidence on new hire wage cyclicality, despite new hires' wages being every bit as sticky as those for existing workers (conditional on match quality). To do that, we derive an expression for the average wage growth of job changers that permits to interpret the semi-elasticity of job changers' wage to changes in unemployment that is implied by the model.

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,  $\nu\bar{\varsigma}_{bt}\xi p_t\bar{b}_t$ . The second type of job changers instead leads to both good-to-bad and good-to-good flows,  $\nu\varsigma_n(1-\xi)p_t\bar{n}_t$  and  $\nu\varsigma_n\xi p_t\bar{n}_t$ . 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 cyclicality of job changers via composition effects. Later, we use empirical moments on the level and cyclicality of the share of bad-to-good flows out of total job flows to discipline the calibration of the model.

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  $c_t^w$  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 let  $\delta_{GB,t}$  be the share moving from good to bad matches. Then to a first order (see the Appendix for details) we can express average wage growth for changers:

$$\bar{g}_t^{EE} = \tilde{g}^{EE} + (1 - \omega)\bar{g}_t^w + \omega\hat{c}_t^w \quad (49)$$

with

$$\bar{g}_t^w = \hat{w}_t - \hat{w}_{t-1} \quad (50)$$

$$\hat{c}_t^w = \pi_{BG}\hat{\delta}_{BG,t-1} - \pi_{GB}\hat{\delta}_{GB,t-1} \quad (51)$$

where  $\hat{z}_t$  denotes log deviations of variable  $z_t$  from steady state and  $\omega \in [0, 1)$  is the steady state share of average job changer wage growth that is due to changes in match quality. As shown in the Appendix, the parameters  $\omega$ ,  $\pi_{BG}$ , and  $\pi_{GB}$  are all positive and are functions of model primitives.

Equation (49) indicates that average wage growth for job changers is a convex combination of average wage growth for existing workers and a composition component. Absent the composition effect (i.e. if  $\omega = 0$ ), average wage growth for job changers would look no different than for continuing workers. With the composition effect present, however, cyclical variation of the composition of new match quality enhances the relative volatility of job changers wages.

In particular, the cyclical composition effect  $c_t^w$  varies positively with the share in total job flows of workers moving from bad to good matches,  $\delta_{BG,t-1}$ , and negatively with the share moving from good to bad,  $\delta_{GB,t-1}$ . As we have discussed, the search intensity by workers in bad matches,  $\bar{\varsigma}_{bt}$ , is highly procyclical, leading to  $\delta_{BG,t-1}$  being procyclical and  $\delta_{GB,t-1}$  countercyclical. The dynamics of the shares also depends on the average firm composition,  $\bar{\gamma}_t$ , determining the relative stocks of bad and good matches available to make a job-to-job transition. During expansions composition slowly improves ( $\bar{\gamma}_t$  decreases) so that over time less workers in bad matches remain available to make a bad-to-good transition and more workers in good matches can make a good-to-bad transition. Specifically, after substituting the expressions for the flow shares (see the Appendix for details), the compositional component can be rewritten as

$$\widehat{c}_t^w = \pi_\varsigma \widehat{\varsigma}_{bt-1} + \pi_\gamma \widehat{\gamma}_{t-1} \tag{52}$$

where the parameters  $\pi_\gamma$  and  $\pi_\varsigma$  are positive and functions of model primitives. In the next section, we show that the net effect of procyclical search intensity and countercyclical composition is that  $c_t^w$  is procyclical, i.e. the composition effect on job changers' enhance wage growth in good times and weakens it in bad times. In this way the model can produce the kind of cyclical movements in match quality that can lead to estimates of new hire wage cyclicity 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 though new hires' wages have the exact same cyclicity as for existing workers.

## 4 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 cyclicity of new hires' versus continuing workers' wages. We first describe the calibration before turning to the results.

## 4.1 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,  $\beta$ ; the capital depreciation rate,  $\delta$ ; the “share” of labor in the production technology,  $\alpha$ ; and the autoregressive parameter and standard deviation for the productivity process,  $\rho_z$  and  $\sigma_z$ . Our parameter choices are standard:  $\beta = 0.99^{1/3}$ ,  $\delta = 0.025/3$ ,  $\alpha = 1/3$ ,  $\rho_z = 0.95^{1/3}$ , and  $\sigma_z = 0.007$ .<sup>35,36</sup>

Four more parameters are specific to the search literature. Our choice of the matching function elasticity with respect to searchers,  $\sigma$ , is 0.4, guided by the estimates from Blanchard and Diamond (1989). We set the worker’s bargaining power  $\eta$  to 0.5, as in GT. We normalize the matching function constant,  $\sigma_m$ , to 1.0. We choose  $\lambda$  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 4.

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,  $\phi$ ; the probability that a new match is good,  $\xi$ ; the elasticity of the search cost,  $\eta_\zeta$ ; the hiring cost parameter,  $\kappa$ ; the separation probability,  $(1 - \nu)$ ; the scale parameter of the search cost,  $\varsigma_0$ ; 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 cyclicality 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  $\phi$  to target the average wage change of workers making direct job-to-job transitions in our data, 4.5 percent (see Table 2, column 3); holding everything constant, a higher  $\phi$  implies a smaller (positive) average percentage wage increase for job changers.

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<sup>35</sup> Note that, in contrast to the frictionless labor market model, the term  $\alpha$  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  $\alpha$ , here we simply follow convention by setting  $\alpha = 2/3$ .

<sup>36</sup> The parameter  $\sigma_z$  is chosen to target the standard deviation of output.

We recover  $\phi = 0.79$ . We calibrate  $\xi$  to match the average share of job transitions involving positive wage changes out of total job flows in our data, 0.527. Holding fixed the targeted transition probabilities, a lower  $\xi$  corresponds to a higher steady state value of  $\gamma$ , and hence a higher average share of bad-to-good flows. We recover  $\xi = 0.285$ . We calibrate  $\eta_\zeta$  to match the cyclicalty of the share of bad-to-good flows, measured as the coefficient from a regression of the bad-to-good flow share on unemployment (presented at the end of Section 2),  $-1.40$ ; a higher  $\eta_\zeta$  corresponds to a lower elasticity of search intensity to changes in the expected gain from on-the-job search (see equation (32)), and thus, other things equal, to a lower cyclicalty of bad-to-good flows. We obtain  $\eta_\zeta = 1.085$ .<sup>37</sup>

We calibrate the separation probability  $(1 - \nu)$  to match the empirical EU probability of 0.025. The hiring cost parameter  $\kappa$  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  $\tilde{p}$  (where  $\tilde{z}$  denotes steady state of a variable  $z$ ) to match the monthly UE transition probability, 0.42; and then calibrate  $\kappa$  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  $\varsigma_0$  to match an EE probability of 0.025; we obtain  $\varsigma_0 = 1.65$ .<sup>38</sup>

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

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

where  $\tilde{a} = (1 - \alpha)\tilde{y}/\tilde{l}$ . 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  $\phi$ , through a lower disutility of labor.<sup>39</sup> 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 5. 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

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<sup>37</sup> This is close to a quadratic search cost function parameterization and similar to Lise (2013) and Christensen *et al.* (2005).

<sup>38</sup> The values for the EU, EE and UE probabilities are from Lise and Robin (2017).

<sup>39</sup> 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.

cyclical properties of aggregate unemployment and wages. Second, we assess the ability of the model to generate the correct relative cyclicality in wage growth for job changers versus continuing workers.

## 4.2 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 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 3. 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 6 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 output, wages, employment, unemployment, 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 (4.52 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, and we simulate the model to generate time series for unemployment rates and wages of new hires and continuing workers. We 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 (4), where we allow separate terms for new hires from unemployment and non-employment. Both equations are specified in first differences and the computed coefficients are interpreted using the structural equation we have developed in Section 3.7.

Results for the first exercise are given in Table 7, where we compare the results from the SIPP panel data (the first column) with those obtained from data from our model with wage contracts fixed for four quarters on average (the second column), and flexible wages (the third column). The calibrated model with staggered contracting generates (untargeted) wage semi-elasticities similar to the coefficient estimates from the SIPP, for both continuing workers ( $-0.52$  in the model versus  $-0.46$  in the data) and new hires ( $-0.92$  versus  $-1.12$ ). 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.

In the last column we explore the implications of period-by-period Nash bargaining 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 8 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 cyclicality 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  $-1.26$ , only moderately below the coefficient of  $-1.84$  estimated in the SIPP data.<sup>40</sup>

Figures 4 and 5 illustrate how compositional effects influence wage dynamics. We repeat the experiment of a one percent increase in TFP. Figure 4 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.<sup>41</sup>

Figure 5 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 equations (49), (50), and (51). 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 job flows moving from bad to good matches.

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<sup>40</sup> We note that in the numerical results we also recover an indirect composition effect that lends additional cyclicity 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 8.

<sup>41</sup> 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.

## 5 Composition Effects: Extensions and Issues

We have demonstrated how composition bias can account for excess wage cyclicality of new hires versus continuing workers. In this section we first consider two alternative measures of the cyclicality of labor costs. The first is Kudlyak’s (2014) measure of the user cost of labor. The second is Beaudry and DiNardo’s (1991) implicit contracts framework which relates wages to starting unemployment. We show in each case that the evidence of strong wage flexibility could be entirely the product of not adjusting for composition bias. Finally, we elaborate on the case in favor of our baseline assumption that composition effects are absent in the measured wage cyclicality of new hires from unemployment.

### 5.1 Estimating the Cyclicity of the User Cost of Labor

Kudlyak (2014) finds excess cyclicality in her measure of the user cost of labor relative to hiring wages. While one common interpretation of this finding is contractual wage flexibility for new hires along with subsequent wage smoothing, we argue that this empirical pattern can alternatively be generated by composition effects.

Accordingly, we proceed to describe how failure to adjust for composition leads to significant cyclical bias in Kudlyak’s measure of the marginal cost of labor. As we discussed in Section 2, the user cost is the sum of the new hire wage and 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  $t + 1$ . Accordingly, we can express the measured unit cost of labor unadjusted for composition effects,  $ucl_t^m$ , as

$$ucl_t^m = \underbrace{w_{t,t}^m}_{\text{hiring wage}} + E_t \left\{ \underbrace{\sum_{s=1}^{\infty} (\rho\beta)^s (w_{t,t+s}^m - w_{t+1,t+s}^m)}_{\equiv f_t} \right\} \quad (53)$$

where  $w_{t,t}^m$  is the measured wage unadjusted for composition. By contrast, as we showed earlier, the true user cost of labor in our staggered Nash bargaining setting is simply the current wage:

$$ucl_t = w_t \quad (54)$$

where, adjusting for productivity,  $w_t$  is the same for both new hires and existing workers.

To illustrate how not controlling for composition can generate spurious cyclicality in the measured user cost, we proceed as follows: We derive an expression for the measured user cost of labor that would arise in our model (and is unadjusted for composition). To do that we evaluate equation (53) at the average of wages taken over workers who are heterogeneous in term of their match quality. In doing so, we need to account for both the composition

of new hires at the time of the hire and for how such composition evolves over time due to different survival rates of workers employed in good and bad matches.

Let  $\gamma_t^m$  denote the composition of new hires in  $t$  and  $\gamma_{t,t+s}^m$  the composition of workers employed at  $t+s$  among those who were new hires in  $t$ , with  $s = 1, 2, 3, \dots$ . The latter can be expressed recursively as follows:

$$\gamma_{t,t+s}^m = \begin{cases} \gamma_t^m & \text{if } s = 1 \\ \gamma_{t,t+s-1}^m \frac{\rho_{t+s-1}^b}{\rho_{t+s-1}^n} & \text{if } s > 1 \end{cases} \quad (55)$$

where  $\rho_t^b$  and  $\rho_t^n$  are the time  $t$  retention rates of workers employed in bad and good matches.

Let  $w_{t,t+s}^m$  denote the average wage of workers employed at  $t+s$  among the newly employed workers in  $t$  (or among the new hires in  $t-1$ ).<sup>42</sup> This is given by

$$w_{t,t+s}^m = c_{t-1,t+s}^m w_{t+s} \quad (56)$$

with

$$c_{t,t+s}^m = \frac{1 + \phi \gamma_{t,t+s}^m}{1 + \gamma_{t,t+s}^m} \quad (57)$$

where  $\frac{1}{1 + \gamma_{t,t+s}^m}$  is the fraction of employed in good matches at  $t+s$  among new hires at  $t$  and where  $w_t$  is the wage per unit of labor quality at  $t$ . We can then insert the expressions for  $w_{t,t+s}^m$  and  $c_{t,t+s}^m$  into equation (53) to obtain an expression for the measured user cost of labor.

Loglinearizing the last expression and simplifying, it is possible to write the measured user cost as the sum of two components:

$$\widehat{ucl}_t^m = \widehat{w}_t + \widehat{c}_t^{ucl} \quad (58)$$

with

$$\widehat{c}_t^{ucl} = \frac{\rho\beta}{1 - \rho\beta} \Psi \left[ \left( \widehat{\gamma}_t^m - \frac{1}{\rho\beta} \widehat{\gamma}_{t-1}^m \right) + \left( \widehat{\rho}_t^n - \widehat{\rho}_t^b \right) \right] \quad (59)$$

and

$$\Psi = \frac{(1 - \phi) \gamma^m}{(1 + \gamma^m) (1 + \phi \gamma^m)}$$

where the first component in equation (58) is the true user cost of labor,  $w_t$ , and the second is a compositional component,  $c_t^{ucl}$ .

The compositional component has two terms appearing in the squared bracket in equation (59). The first term accounts for the relative evolution of composition of new hires at

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<sup>42</sup> Recall that the timing assumption in our model is that it takes one period for new hires to start working, so that the wages of the *newly employed workers in  $t$*  depend on the composition of the *new hires in  $t-1$* .

time  $t - 1$  (determining composition of newly employed at  $t$ ) and discounted composition of new hires at time  $t$  (determining composition of newly employed at  $t + 1$ ). Since composition is countercyclical, the first component makes  $c_t^{ucl}$  procyclical. The second term reflects the differential cyclicity of the retention rates of workers employed in good and bad matches, in turn determining how the composition of new hires at  $t$  evolves over time. Due to procyclical search intensity, workers employed in bad matches leave their current match at a more procyclical rate than workers employed in good matches, that is,  $\rho_t^b$  is more countercyclical than  $\rho_t^g$ . As a consequence, the second component also makes  $c_t^{ucl}$  procyclical.

We then use our baseline model of Sections 3 and 4 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 hiring wage  $w_t$  plus the compositional component  $c_t^{ucl}$ . We calculate the semi-elasticity to unemployment of both measures and obtain  $-0.66$  for the true user cost and  $-2.49$  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.<sup>43</sup>

## 5.2 Estimating the Effect of the Starting Unemployment Rate on Wages

Beaudry and DiNardo (1991) present evidence that an alternative cyclical indicator, the unemployment rate at the time of hiring, has independent explanatory power for wages. Much of the subsequent literature has interpreted their finding as supportive of contractual wage flexibility at the start with subsequent wage smoothing: It would be implied, for example, by a theory of implicit contracts where incumbent workers are insured against aggregate risk. Here, we note that with cyclical composition, the starting unemployment rate will be predictive of wages absent any role for history dependence and contractual wage flexibility at the start.

In our model, during booms the share of workers hired in good matches increases due to an expansion of workers in bad matches engaging in selective on-the-job search. Hence, as in Hagedorn and Manovskii (2013), there is a negative relationship between wages and the starting unemployment rate through cyclical variation in match quality for workers making a direct employment to employment move. While our model generates a direct relationship of the starting rate and wages only for new hires from employment, because the effect is identified from differenced starting rates and wages, our estimates will also suggest a starting rate effect for new hires from unemployment. To be clear, the model implies no correlation between the wages of new hires from unemployment and the starting rate; but

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<sup>43</sup> Consistently with Kudlyak's estimates, the cyclicity of the measured user cost implied by our model is higher than the cyclicity of new hire wages, not adjusted for composition ( $= -1.44$ ).

for the subset of workers who find a job from employment at some point in the sample period, there will be a negative relation between the terms differenced from the wage and starting unemployment rate, translating to a negative correlation between differenced log wages and starting rates.<sup>44</sup>

To demonstrate the role of the starting rate under cyclical composition, we estimate the following regression equation in first difference with data from the SIPP and simulated data from our model:

$$\begin{aligned} \Delta \log w_{ijt} = & \Delta x'_{ijt} \pi_x + \pi_n^{EE} \cdot \mathbb{I}(EE_{ij}) + \pi_n^{ENE} \cdot \mathbb{I}(ENE_{ij}) \\ & + \pi_{su}^{EE} \cdot \Delta u_{ij}^s \cdot \mathbb{I}(EE_{ij}) + \pi_{su}^{ENE} \cdot \Delta u_{ij}^s \cdot \mathbb{I}(ENE_{ij}) + e_{ijt} \end{aligned} \quad (60)$$

where  $\Delta u_{ij}^s$  represents the differenced starting unemployment rate associated with the current job  $j$  of individual  $i$ .<sup>45</sup> Results are given in Table 9. In both the model and in the data we find quantitatively important starting rate effects for both  $EE$  and  $ENE$  workers, with a smaller effect for workers from non-employment. Hence, the model is able to account for a negative effect of the starting unemployment rate on wages, both for jobs found within and across employment cycles. Notably, this effect is generated solely from cyclical composition, without contractual wage flexibility for new hires and history dependence.

### 5.3 Composition Effect for New Hires from Unemployment

The baseline assumption for the empirical analysis is that the distribution of viable matches available to a worker searching from unemployment is largely invariant to the cycle. Under this baseline, we can interpret the wage cyclicity of new hires from unemployment as a measure of composition-free wage cyclicity. We thus interpret our finding – that the estimated coefficient for  $ENE$  is not statistically different from zero – as evidence that the wages of new hires are no more flexible than the wages of existing workers. This baseline assumption is no more restrictive than that of Hagedorn and Manovskii (2013), who assume an invariant wage distribution; and less restrictive than Kudlyak (2014), who assumes no role for cyclical composition for any new hires.

Nonetheless, our interpretation of the data could be sensitive to deviations from our

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<sup>44</sup> Hagedorn and Manovskii (2013) introduce alternative controls to eliminate the explanatory power of the starting unemployment rate. These controls, however, are designed only to capture variation in the starting rate for jobs found within an uninterrupted employment cycle, i.e. jobs found from employment. Hence, the finding of Basu and House (2017) of a robust starting rate effect despite the inclusion of the Hagedorn and Manovskii controls does not necessarily point to a role for contractual wage flexibility at the start of a match.

<sup>45</sup> Note the different notation from that in Section 2.4, where we use  $EE_{ijt}$  and  $ENE_{ijt}$  to denote new hires at job  $j$  and time  $t$  from employment and non-employment. Here, we use  $EE_{ij}$  and  $ENE_{ij}$  to identify workers at job  $j$  hired from employment or non-employment at any point of their tenure at the job.

baseline assumption. Conceivably, although the cyclical composition bias associated with job-changers overstates new hire wage cyclicality, some other form of cyclical composition bias may understate the wage cyclicality of new hires from unemployment. Were this the case, our baseline assumption would lead us to falsely reject excess wage cyclicality of new hires. As we will make clear, our view of the literature is that, if anything, our baseline assumption works against us: To the extent that there is cyclical selection of unemployed workers, the type of selection that finds broadest support in the literature would lead to a procyclical bias in the estimates of wage cyclicality of new hires from unemployment. Indeed, in the Appendix we perform a number of robustness exercises controlling for the type of selection emphasized in the literature and our results become stronger.

Cyclical selection of workers from unemployment can be broadly classified into two types: (*i*) ex-post selection on the basis of realized match quality; and (*ii*) ex-ante selection on the basis of firm/worker characteristics that exist prior to matching.

The theoretical argument for selection on ex-post match characteristics is as in Mortensen and Pissarides (1994).<sup>46</sup> During a recession, the threshold productivity both for maintaining existing matches and creating new matches increases, and hence, matches that would be viable during an expansion do not remain so during a recession. Notably, this type of selection operates both through job creation and through job destruction. Both margins matter for our estimates of new hire wage cyclicality, as the coefficient is identified from differences in wages across jobs. To the extent that workers hired from unemployment during a recession are systematically hired into better matches, as hiring standards tighten in bad times, this type of selection has the potential to understate the wage declines of new hires from unemployment during recessions, generating downward bias in our estimates of new hire wage cyclicality. Conversely, 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, generating upward bias. Hence, the overall impact of selection on the basis of ex-post match characteristics is ambiguous, with the potential to generate either countercyclical or procyclical bias in the true extent of wage cyclicality of new hires from unemployment.

Not only is the net effect of cyclical selection on ex-post match characteristics a priori ambiguous: A literature evaluating the quantitative importance of these various margins of selection suggests that it must play only a minor quantitative role for generating a countercyclical bias in both average wages of new hires and average past wages of workers in unemployment. Barlevy (2002) studies a DMP model with ex-post match heterogeneity and on-the-job search to assess the match quality effects of countercyclical hiring standards

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<sup>46</sup> To be clear, Mortensen and Pissarides abstract from endogenous hiring standards by assuming that all new matches are created with the highest match productivity. This assumption can be relaxed, as in Barlevy (2002).

versus procyclical self-selection of workers searching on-the-job.<sup>47</sup> He finds that the former mechanism is of minor importance. Mueller (2017) documents considerable evidence that in recessions the pool of unemployed shifts toward workers with high wages in their previous job. He then shows that a plausibly calibrated DMP model with idiosyncratic match quality and endogenous job destruction can only generate compositional shifts that are tiny in magnitude.<sup>48</sup> Mueller then argues that a plausible explanation for the composition shifts documented 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). By doing so, we rule out this latter avenue for composition effects.

The second form of cyclical selection stems from selection on the basis of ex-ante characteristics. Here, the selection mechanisms that have been highlighted in the theoretical literature induce a procyclical bias, which would lead us to overstate the cyclicity of wages from new hires from unemployment. Further, as we discuss, a way to control for this bias is to allow for occupational controls. When we do so, our result that there is no new hire effect on wage flexibility only becomes sharper.

Selection on ex ante characteristics is possible when workers and firms are ex-ante heterogeneous in their characteristics, and some workers/firm matches are more productive than others. Procyclical bias emerges in the following scenario: In recessions, firms facing lower job values tighten hiring standards and workers facing lower job-finding rates accept less productive jobs so that, for a given worker, the distribution of viable matches may be worse during a recession. A notable example of such mechanisms is Moscarini (2001), where slack labor market conditions compel workers to select less on comparative advantage and accept less productive jobs.<sup>49</sup> Similarly, the empirical literature on ex-ante heterogeneity has presented compelling evidence of systematic selection of workers to worse jobs during recessions, specifically with regard to selection on the basis of occupation. Sahin *et al.* (2014), for example, document countercyclical “mismatch” unemployment, whereby workers have a more difficult time finding a suitable job during a recession. They find that the most important type of mismatch unemployment is along the dimension of occupation, suggesting that the marginally employed worker is more likely to be “occupationally mismatched” during a recession.<sup>50</sup>

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<sup>47</sup> In Barlevy’s model, match quality is the outcome of the match of exogenous worker/firm types. But given the random matching and the assumed uniform distribution of worker and firm types, the set-up is equivalent to selection on ex-post match characteristics.

<sup>48</sup> In the Appendix, Mueller (2017) shows that this finding is robust to numerous modeling assumptions.

<sup>49</sup> Other papers where cyclical ex-ante heterogeneity worsens the set of matches available to a searching worker include Menzio and Shi (2010), where a subset of employed workers direct their search towards lower-value matches during recessions; Moscarini and Postel-Vinay (2013), where higher-wage firms post fewer vacancies during a recession; and Huckfeldt (2016), where firms posting high-quality jobs hire more selectively during recessions.

<sup>50</sup> This interpretation is confirmed by subsequent research. For example, Huckfeldt (2016) documents

To the extent that the literature has emphasized possible cyclical selection of workers from unemployment, the type of selection that has found most empirical support generates a procyclical composition bias, in turn largely mediated by selection on the basis of occupations. What this suggests is that occupational variables can be used to control for selection effects. In the Appendix, we test the robustness of our results with the inclusion of controls for new hires who switch occupation in a subsequent job; and we assess how the average duration of unemployment for ENE workers affects our estimates of new hire wage cyclicality. We find that our main finding of no new hire effect on wage cyclicality is reaffirmed (and increases in statistical significance) when we include controls for these alternative sources for cyclical selection.

## 6 Concluding Remarks

We present panel data evidence suggesting that the excess cyclicality 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 cyclicality of new hire wages, appears to be driven entirely by procyclical job upgrading and not true wage flexibility. Indeed, we present also evidence to show that net flows from bad to good matches are procyclical, consistent with the idea that cyclical upgrading accounts for much of the variation in wages of job changers.

We reinforce the idea that the observed excess cyclicality 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 procyclical of job quality in new matches that stems from workers 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

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that workers who are displaced to unemployment during a recession are more likely to find re-employment in a lower paying occupation than workers displaced during an expansion. Hershbein and Kahn (2018) use vacancy-level data to show that, for a given job, firms direct vacancies towards workers of high-skill when the labor market is slack, particularly for “middle-skill” occupations.

(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 *e 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: “Standard regression” (e.g. Bils, 1985) and the new hire effect

	1990-2012 sample	
	(1)	(2)
Unemployment rate	-0.147** (0.0605)	-0.461*** (0.0967)
Unemp. rate · $I(\text{new})$	-1.643*** (0.3264)	-1.122** (0.4606)
$I(\text{new})$	-0.011*** (0.0017)	0.010** (0.0040)
Estimator	Fixed Effects	First Differences
No. observations	378,670	321,404
No. individuals	57,266	57,266
No. new hires	18,091	21,855

Robust standard errors in parenthesis

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

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

	FE		FD	
	(1)	(2)	(3)	(4)
UR	-0.145** (0.0609)	-0.145** (0.0609)	-0.428*** (0.0967)	-0.423*** (0.0967)
UR · $\mathbb{I}(EE)$	-1.979*** (0.5042)	-1.934*** (0.4726)	-1.840*** (0.6790)	-1.642*** (0.6215)
UR · $\mathbb{I}(ENE)$	-0.340 (0.5386)	0.045 (0.5956)	-0.437 (0.6639)	-0.546 (0.7346)
$\mathbb{I}(EE)$	0.004* (0.0023)	0.001 (0.0022)	0.045*** (0.0048)	0.038*** (0.0046)
$\mathbb{I}(ENE)$	-0.030*** (0.0029)	-0.034*** (0.0034)	-0.047*** (0.0066)	-0.065*** (0.0074)
$P(\pi_{nu}^{EE} = \pi_{nu}^{ENE})$	0.023	0.008	0.135	0.250
Unemp. spell for ENE	0+	1+	0+	1+
No. observations	375,645	375,645	375,645	375,645
No. individuals	56,879	56,879	56,879	56,879
No. EE new hires	9,855	11,433	9,855	11,433
No. ENE new hires	6,437	4,859	6,437	4,859

Robust standard errors in parenthesis

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

Table 3: Wage-improving job changes: statistics

	Fraction	Average change	Wage residual, prior to job-change
$\Delta \log w > 0$	0.527	0.304	-0.247
$\Delta \log w < 0$	0.473	-0.230	0.057

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

Table 4: Calibration

Parameter values		
Discount factor	$\beta$	$0.997 = 0.99^{1/3}$
Capital depreciation rate	$\delta$	$0.008 = 0.025/3$
Production function parameter	$\alpha$	0.33
Technology autoregressive parameter	$\rho_z$	$0.983 = 0.95^{1/3}$
Technology standard deviation	$\sigma_z$	0.007
Elasticity of matches to searchers	$\sigma$	0.4
Bargaining power parameter	$\eta$	0.5
Matching function constant	$\sigma_m$	1.0
Renegotiation frequency	$\lambda$	11/12 (4 quarters)

Table 5: Jointly calibrated parameters

Parameter	Description	Value	Target
$\phi$	Inverse productivity premium	0.79	Average E-E wage increase (4.5%)
$\xi$	Prob. of good match	0.28	Wage-improving job changes ( $\tilde{\delta}_{BG} = 0.53$ )
$\eta_\varsigma$	Search cost elasticity	1.09	$\eta_{\delta_{BG,t}, u_t}$ (-1.40)
$\kappa$	Hiring cost parameter	71.27	U-E probability (0.42)
$1 - \nu$	Separation probability	0.025	E-U probability (0.025)
$\varsigma_0$	Scale parameter of search cost	1.65	E-E probability (0.025)
$u_B$	Flow value of unemployment	2.59	Relative value, non-work (0.71)

Table 6: 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	4.52	9.47
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	1.35	3.68
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 7: Wage semi-elasticities: All new hires

Semi-elasticities of wages w/r.t. unemployment			
	SIPP	Model, 4Q	Model, flex
UR	-0.46 (0.097)	-0.52	-6.97
UR · $\mathbb{I}(\text{new})$	-1.12 (0.461)	-0.92	-6.17

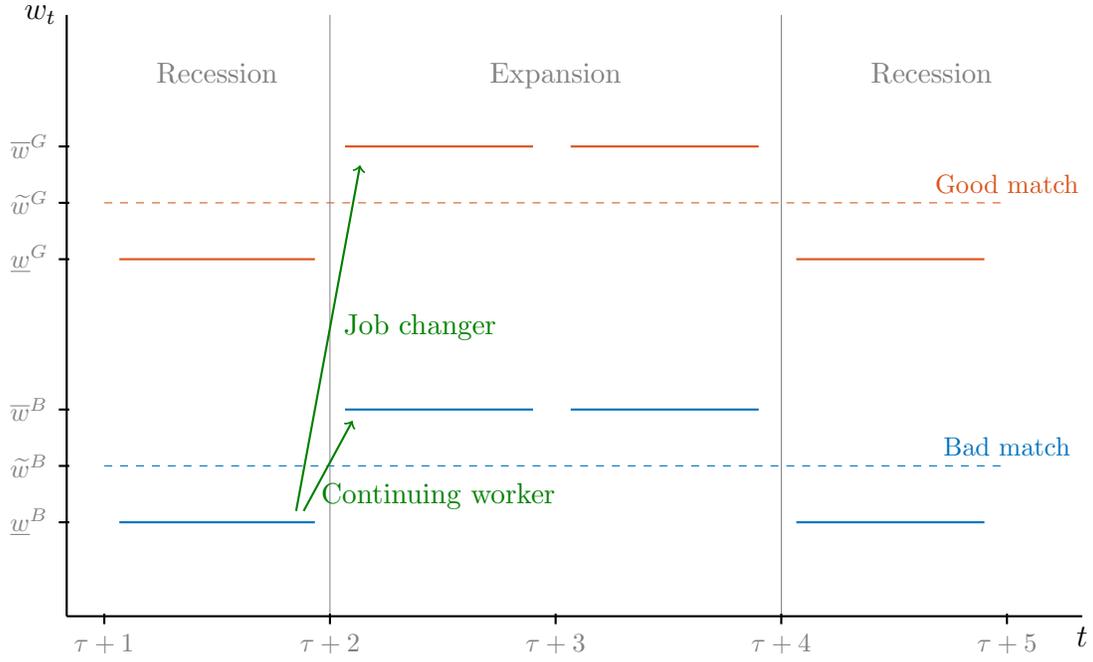
Table 8: Wage semi-elasticities: EE vs. ENE

Semi-elasticities of wages w/r.t. unemployment			
	SIPP	Model, 4Q	Model, flex
UR	-0.43 (0.097)	-0.52	-6.97
UR · $\mathbb{I}(EE)$	-1.84 (0.680)	-1.26	-5.41
UR · $\mathbb{I}(ENE)$	-0.44 (0.664)	-0.60	-6.52

Table 9: Wage semi-elasticities w/r.t. starting unemployment rate

	SIPP	Model, 4Q
$\pi_{su}^{EE}$	-1.02 (0.220)	-2.20
$\pi_{su}^{ENE}$	-0.87 (0.399)	-1.02

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 3: Impulse responses to productivity shock

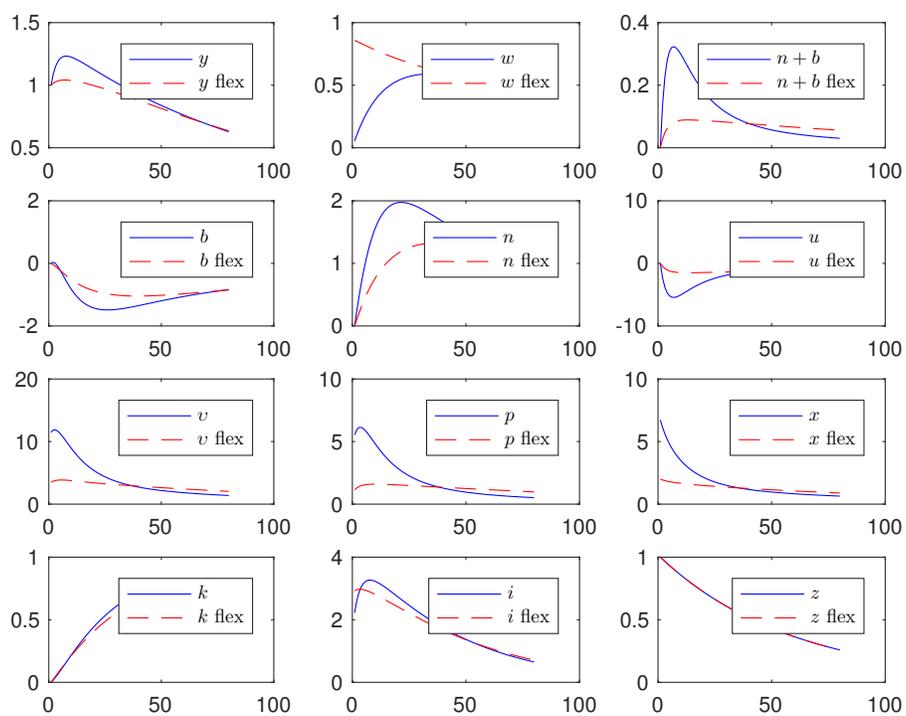


Figure 4: Labor market composition and job flows

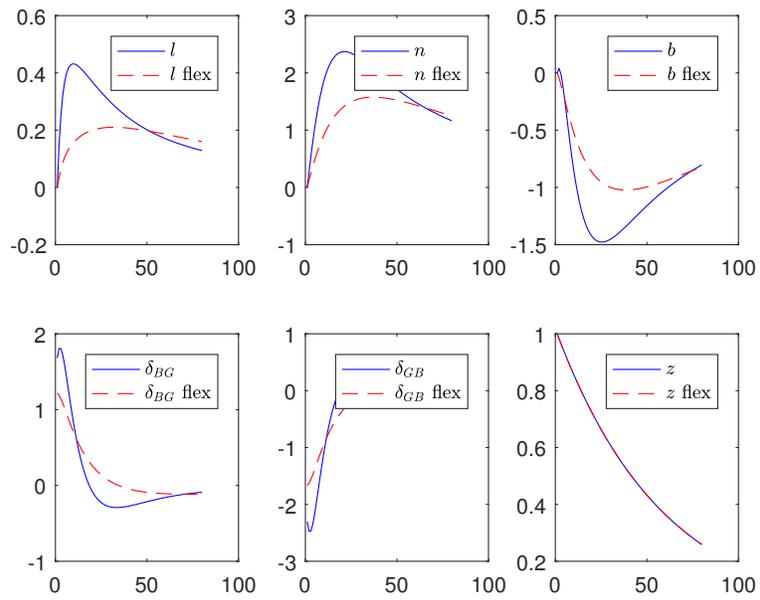


Figure 5: Wage growth and components

