Unemployment Fluctuations, Match Quality, and the Wage Cyclicality of New Hires

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Abstract

Recent papers interpret micro-level findings of greater cyclicality in the wages of new hires as evidence for flexible wages of new hires, thus concluding that wage rigidity is not an empirically plausible mechanism for resolving the unemployment volatility puzzle. We analyze data from the Survey of Income and Program Participation (SIPP) to argue that greater cyclicality of wages for new hires reflects compositional effects and not greater wage flexibility. After controlling for (i) whether a new hire comes from unemployment or other another job and (ii) cyclical movements in match quality for job changers, we find no evidence for greater wage flexibility among new hires. In light of our empirical findings, we develop an equilibrium model of unemployment with staggered Nash wage bargaining, heterogeneous match quality, and on-the-job search. Workers in bad matches vary their search intensity according to the probability of finding a better match, generating cyclicality in the contribution of bad-to-good transitions to total job-to-job flows. Using simulated data from our model, we compute measures of new hire wage cyclicality analogous to those found in the literature and show that cyclical match composition in our model generates spurious evidence of new hire wage flexibility of comparable in magnitude to what we estimate from the SIPP. The model is also successful in accounting for the cyclicality of aggregate wages and the dynamics of aggregate unemployment.

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. The approach traces to the early large scale macroeconometric models and remains prevalent in the recent small scale DSGE models.[1] It has also been true for searching and matching models of the labor market in the tradition of Diamond, Mortensen and Pissarides. For example, Shimer (2005) and Hall (2005) show that incorporating wage rigidity greatly improves the ability of these models to account for unemployment fluctuations.[2]

An important recent 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 wages of new hires, which need 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 wages of new hires appear substantially more flexible than those of existing workers. Pissarides then interprets this evidence as suggesting that the relevant measures suggest a high degree of wage flexibility, calling into question efforts to incorporate wage rigidity into macroeconomic models.

In this paper we revisit the issue of the flexibility of new hires' wages and the associated implications for aggregate unemployment fluctuations. We first present fresh evidence on new hire wage cyclicality using a detailed new panel data set. We then develop a quantitative macroeconomic model that is able to account for both the aggregate and panel data evidence. We first show that with our panel data we can reproduce estimates found in the literature: new hires wages' appear more cyclical than those for existing workers. We then show that once one controls for certain cyclical composition effects, the wages of new hires are no more flexible than the wages of existing workers.

We do two types of controls for composition effects. First, following Haefke, Sonntag, and van Rens (2013), we distinguish between new hires coming from unemployment and those who are changing jobs. Here we find no new hire effect for workers coming from unemployment: the estimates suggest that the wages of these workers are no more cyclical than those for continuing workers.[3]

[1] See for, example, Christiano, Eichenbaum and Evans (2005), Smets and Wouters (2007), Gertler, Sala and Trigari (2008), Gali, Smets and Wouters (2012), and Christiano, Eichenbaum and Trabandt (2014).

[2] Gertler and Trigari (2009), Hall and Milgrom (2008), and Blanchard and Gali (2010) build on this approach and model the wage setting mechanism in greater detail.

[3] Our findings slightly contrast with those of Haefke, Sonntag and van Rens, who use pure cross-sectional

While the new hire effect disappears for workers coming from unemployment, it remains for job changers. We view this result as a reminder that much of the evidence of a new hire effect comes from data sets where job changers account for the lion's share of new hires.[4] Since an important reason workers change jobs is to improve job quality, wage movements for job changers could reflect job quality shifts as opposed to differences in wage flexibility. Indeed, we show that once we control for job quality, the new hire effects disappears, even for job changers.

Our emphasis on the role of composition in explaining the wage cyclicality of new hires is not new. It is fair to say that the standard interpretations of the evidence prior to Pissarides involved some form of composition effect involving procyclical fluctuations in the quality of new job openings. The particular mechanism we find appealing involves cyclical fluctuations in job match quality, as originally suggested by Barlevy (2002). In Barlevy's framework, workers in bad matches are more likely to find good matches in booms than in recessions. Thus the cyclical new hire effect in wages reflects procyclical upgrading of match quality by job changers as opposed to greater flexibility of new hire wages. Note that this mechanism applies best to job changers and thus can account for why the apparent new hire effect is present for workers making direct job-to-job-transitions, but not for workers hired from unemployment.

To drive home this point, we develop a search and matching model with wage rigidity in the form of staggered wage contracting, variable job match quality, and on-the-job search. We show that the model is consistent with both the aggregate data and the panel data evidence. All the ingredients we add are critical for achieving this consistency. One interesting implication of the model is that it produces job reallocation, leading to a kind of sullying effect of recessions, as originally conceived by Barlevy.

Section 2 provides the new panel data evidence. Section 3 describes the model and Section 4 presents the numerical results. Concluding remarks are in Section 5.

2 Data and Empirics

This section presents new evidence on the wage cyclicality of new hires. We do so using a rich new data set. We first show that we are able to replicate the existing evidence showing greater cyclicality of the wages of new hires relative to existing workers. We then proceed to show

data and recover point estimates that are suggestive of greater wage cyclicality of new hires, but not statistically significant. We suspect that the panel aspect of our data permits sharper controls for unobserved heterogeneity and compositional effects.

[4] Indeed, Bils (1985) uses the term "job changers" as opposed to "new hires" and interprets his results as applying to the former.

that (i) there is no new hire effect for workers coming from unemployment (as opposed to those changing jobs) and (ii) after controlling for job match quality, there is also no new hire effect for job changers. Put differently, the evidence is consistence with new hires having the same degree of wage cyclicality as existing workers.

We first describe the data and then move to the estimation.

2.1 Data

We use data from the Survey of Income and Program Participation (SIPP) from 1990 to 2012. The SIPP is administered by the U.S. Census Bureau and is designed to track a nationally representative sample of U.S. households. The SIPP is organized by panel years, where each panel year introduces a new sample of households. Over our sample period the Census Bureau introduced eight panels. The starting years were 1990-1993, 1996, 2001, 2004, and 2008. The average length of time an individual stays in a sample ranges from 32 months in the early samples to 48 in the more recent ones.

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. Although each wave contains data for four months, we restrict our sample to the final wave for observations to mitigate the SIPP "seam effect", whereby survey respondents "project current circumstances back onto each of the four prior months..." (Census Bureau, 2001, pg.1-6).

The main advantages of the SIPP over other commonly used data sets has such as the PSID or the NLSY are that it is larger, more representative of the population, and available at a high frequency (e.g. surveys are every four months as opposed to annually.) The rich high frequency structure allows for precise measures of cyclical job status and wages. It also permits separating new hires from job changers and those coming from the unemployed.

The appendix provides greater detail on the data. It also describes the construction of the variables we use in the estimation.

2.2 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).[5] Let w_{ijt} be the wage of individual i in job j at time t, x_{ijt} individual level characteristics such as education and experience as well as a time trend, u_t the prime age male unemployment rate, $\mathbb{I}(new_{ijt})$ an indicator variable that equals unity if the worker is a new hire and zero if not, and α_i an individual fixed effect. The measurement equation for wages is then given by

$$\log w_{ijt} = x'_{ijt}\pi_x + \pi_u \cdot u_t + \pi_n \cdot \mathbb{I}(new_{ijt}) + \pi_{nu} \cdot \mathbb{I}(new_{ijt}) \cdot u_t + \alpha_i + e_{ijt} \tag{1}$$

where e_{ijt} is random error term.

The inclusion of the unemployment rate in the regression is meant to capture the influence of cyclical factors on wages, while the interaction of the new hire dummy with the unemployment rate is meant to measure the extra cyclicality of new hires wages. In particular, the coefficient π_u can be interpreted as the semi-elasticity of wages with respect to unemployment, while $\pi_u + \pi_{nu}$ gives the corresponding semi-elasticity for new hires. The key finding in the literature is that π_{nu} is negative (along with π_u), suggesting greater cyclical sensitivity of new hires' wages.

At this point we make two observations: First, with exception of Haefke, Sonntag and van Rens (2013), the literature typically does not distinguish between new hires coming from unemployment and those coming from other jobs. Second, there is no attempt to control for estimation bias stemming from cyclical movements in job match quality. We turn to these issues shortly.

We first show that with our data we can obtain the results in the literature. To obtain consistent coefficient estimates of equation (1), it is necessary to account for the presence of unobserved heterogeneity implied by α_i that may be correlated with observables. The convention in the literature, accordingly, is to use either a first difference or a fixed effects estimator, depending on the properties of the error term. The low serial correlation of the error terms in the exercises we perform suggests that the fixed effects estimator is preferred. However, since Bils (1985) and others used a first difference estimator, we show the results are robust to either approach.

The regressions are based on monthly data.[6] For comparability to Bils (1985), we only use

[5] Included among the many studies regressing individual level wages on some measure of unemployment as a cyclical indicator are Barlevy (2001); Beaudry and Dinardo (1991); Deveraux (2001); Hagedorn and Manovskii (2013); Martins, Solon, and Thomas (2012); Shin (1991); and Solon, Barsky and Parker (1994).

[6] While we have monthly information, as we noted earlier we only use wage information from the final month

observations for men between the ages of 20 and 60. As our measure of hourly wages, we use job-specific earnings. 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 a three months average of the monthly PCE. Finally, we define "new hires" as individuals who are in the first four months of their tenure on a job.[7] The appendix provides additional information on variable construction, including the individual level characteristics we use.

Table 1 presents the results. 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 significantly more cyclical than those for existing workers. When estimating the equation in first differences, the semi-elasticity of new hire wages is -1.29, compared to -0.424 for continuing workers. With fixed effects, the new hire semi-elasticity is estimated to be -1.565, compared to -0.317 for continuing workers. In both specifications, the semi-elasticity is significant at the 1% level for continuing workers; and the new hire differential is significant at the 1% level. We find no evidence that the predicted errors from the regressions are serially correlated.[8] Hence in what follows, we apply fixed effects.

While we recover precise coefficient estimates that imply both continuing worker wage cyclicality and a new hire effect, our estimates reveal less cyclicality than most of the existing literature. 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 both PSID and NLSY through 1993 and recovers a semi-elasticity of 3.0 for job changers. We speculate that our lower estimates are due mainly the high-frequency of our data (every four months as opposed to every year). If workers are on staggered multi-period contracts (as will be the case in the quantitative model we present), then a smaller fraction of wages are likely to be adjusted over a four month interval than would be the case annually. In any case, our quantitative model will generate data consistent with the degree of wage cyclicality suggested by the evidence in Table 1.

of each four month wave to avoid the "seam" effect.

[7]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.

[8]In this case, fixed effects is more efficient than first differences.

2.3 Robustness of the New Hire Effect

We now present evidence that the estimated new hire effect in the literature reflects misspecification and not greater wage cyclicality of new hires.

We begin by distinguishing new hires that come from unemployment from those that come from other jobs. As Haefke, Sonntag, and van Rens (2013) emphasize, the hiring margin that is key for generating unemployment volatility in search and matching models with sticky wages is that of workers coming from unemployment, not that of workers making job-to-job transitions. Yet most empirical studies do not distinguish between job-changers and workers hired from unemployment, as in Bils (1985).

Accordingly, it is important to isolate the wage behavior for new hires coming from unemployment. To do so, we estimate a variant of (1) that allows for a separate new hire effect for workers coming from non-employment and workers making direct job-to-job transitions:

$$\begin{aligned}\log w_{ijt} = x'_{ijt}\pi_x + \pi_u \cdot u_t + \pi_{nu}^{ENE} \cdot \mathbb{I}(new_{ijt}\&ENE_{ijt}) \cdot u_t + \pi_{nu}^{EE} \cdot \mathbb{I}(new_{ijt}\&EE_{ijt}) \cdot u_t \\ + \pi_n^{ENE} \cdot \mathbb{I}(new_{ijt}\&ENE_{ijt}) + \pi_n^{ENE} \cdot \mathbb{I}(new_{ijt}\&ENE_{ijt}) + \alpha_i + e_{ijt},\end{aligned} \tag{2}$$

where we use the notation ENE to signify workers with an intervening spell of non-employment and EE to signify workers who made direct job-to-job transitions.

Table 2 presents the results. For robustness, we consider three different measures of what constitutes a new hire from non-employment. In the baseline case presented in the first column we use the broadest measure: all new hires who did not receive a wage in the previous month, independent of how long the unemployment spell. In the second column for ENE transitions we consider only new hires coming from short-term unemployment, which we consider to be a spell four months or less. Here we address the concern that there may be something unusual about the wage behavior of those coming from long-term unemployment, leading us to drop these observations. Finally, the third column addresses the concern that new hires from nonemployment that have only missed one months pay might in fact be job-changers taking a short break between jobs. Accordingly, for this case we lump those new hires with only one month of non-employment with job-changers.

As the table shows, for all three specifications, the new hire effect disappears for workers coming from unemployment. The coefficient π_{nu}^{ENE} is not statistically significant in each case. Thus, for new hires coming from unemployment, wages are no more cyclical than those for existing workers. Along these lines, the estimates of wage cyclicality for existing workers are similar to the baseline case of Table 1. Finally, while the new hire effect disappears for workers coming from unemployment, it remains as strong as it did in the baseline case for job-changers.[9] This result is consistent with our earlier observation that virtually all of the evidence of a new hire effect in the literature comes from data sets dominated by job changers.

We next explore the source of high wage cyclicality of job changers and present some evidence to suggest that compositional effects stemming from variation in job match quality might be at work. Suppose that the error term e_{ijt} in the regression equation (1) takes the form

$$e_{ijt} = q_{ij} + \varepsilon_{ijt} \tag{3}$$

where q_{ij} represents unobserved match quality. If the share in total job flows of workers moving from bad matches to good matches is procyclical, then match quality for new hires should be procyclical. The implication is that q_{ij} should covary negatively with the term that interacts the new hire dummy with the unemployment rate:

$$Cov(q_{ij}, I(new_{ijt}) \cdot U_t) \leq 0, \tag{4}$$

It follows that the error term e_{ijt} will be negatively correlated $I(new_{ijt}) \cdot U_t$. As a consequence, the estimated coefficient intended to identify the excess cyclicality of new hires wages, $\widehat{\pi}_{nu}$, will be biased downward. If so, estimates of a negative value of π_{nu} might simply reflect composition bias rather than greater cyclicality of new hire wages.

We emphasize further that the compositional bias stemming from procyclical match quality is likely greater for job changers than for new hires coming from unemployment. As Barlevy (2002) emphasizes, job upgrading is an important reason for employment-to-employment transitions and this upgrading is highly procyclical. By contrast, a worker coming from non-employment may be more inclined to accept a bad match in a boom, which may dominate the alternative of being unemployed. Further, accepting the bad match does not preclude the worker from trying to find a better one.

One way to control for wage variation that is due to match quality is to allow for a person-job fixed effect. Accordingly, we estimate a variant of equation (1) with a fixed effects at the person-job level, α_{ij}:

$$\log w_{ijt} = x'_{ijt}\pi_x + \pi_u \cdot U_t + \pi_{nu} \cdot \mathbb{I}(new_{ijt}) \cdot U_t + \pi_n \cdot \mathbb{I}(new_{ijt}) + \alpha_{ij} + e_{ijt}. \tag{5}$$

[9] We can reject the null hypothesis that the wage cyclicality for new hires from non-employment equals the wage cyclicality for new hires from employment at the 5% level.

Whereas in the baseline specification there was a single intercept α_i associated with each person, now there is an intercept that captures the interaction of the person with the job.

Figure 1 illustrates how the person-job intercept controls for match quality. The figure portrays wages on two possible jobs for the worker: a high wage job that is a good match and a low wage job that is a bad one. For each job the dotted line is the wage absent cyclical effects. The solid line is the wage including cyclical effects. Suppose the worker starts out in a bad job match and then when the first boom comes, the worker moves to a good match. The worker's wage jumps partly due to cyclical factors but mostly due to improved match quality. Absent a control for match quality, it appear that the worker's wage as new hire was far more cyclical than that of an existing worker. The person-job fixed effect adds this kind of control essentially by removing the component of the wage due to match quality. In term of Figure 1, the fixed effect removes the steady state wage for each job, thus isolating the true cyclical variation.

In this case, we identify the relative wage cyclicality, by comparing the wage behavior of an individual as a new hire with that of the same individual as a existing worker (and doing so for thousands of individuals). To separately identify wage cyclicality of existing workers, it is important that we observe an individual's tenure on a job for a long enough period so that wage changes can be expected to occur. Our data set satisfies this criteria: the average time we observe a worker on a job after being newly hired is 17 months.[10]

Table 4 presents the results with person-job fixed effects. In the first column we do not condition on the type of new hire job transition. In the second we restrict attention to job changers. In the third, we estimate a new hire effect for both job changers and for new hires from non-employment (using our baseline definition of ENE). Across all regressions, we find no significant new hire effect. After controlling for match quality, new hires' wages appear no more flexible than those for existing workers.[11]

In the next section we develop an economic model to sharpen our empirical finding that the new hire effect may be an artifact of an improper econometric specification. In the model we develop, new hires wages are no more flexible than those for existing workers. Yet data generated from the model will be able to generate the appearance of a new hire effect, precisely for the kinds of reasons we have suggested.

[10] Note we cannot recover an estimate of π_{nu} in the extreme case that there is a *permanent* new hire effect wherein wages are permanently indexed to aggregate conditions at match inception, as the new hire effect will be differenced out from the person-job fixed effects. Hagedorn and Manovski (2013) argue that previous evidence that wages were permanently linked to starting conditions via implicit contracts is faulty.

[11] We also note that the estimated semi-elasticity of wages with respect to unemployment for existing workers drops in half once we allow for person-job fixed effects. This reflects that much of the cyclical within-individual wage variation is due to across-job variation in wages.

3 Model

In keeping with a vast literature, 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). As in these papers, we minimize complexity by imposing complete consumption insurance. Our use of the real business cycle model is also meant for simplicity. It will become clear that our central point of how a model with wage rigidity can account for the micro wage evidence will hold in a richer macroeconomic framework.

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 Gertler and Trigari (GT, 2009). Second, we allow for both variable match quality and on-the-job search with variable search intensity. These features will generate procyclical job ladder effects, in the spirit of Barlevy (2002). 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 ϕ of that of a good match, where $\phi \in (0, 1)$. Let n_t be the number of good matches within a firm that are working during period t and b_t the number of bad matches. Then the firm's effective labor force l_t is the following composite of good and bad matches:

$$l_t = n_t + \phi b_t \tag{6}$$

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

Workers search for jobs both when they are unemployed and when they are employed. Before search occurs, matches are subject to an exogenous separation shock. With probability ν, workers will search on-the-job; absent successful search that generates a new match at a different firm, these workers will remain at the firm for another period. With probability $1-\nu$, the match is terminated. Workers who are subject to a separation shock and do not successfully find a job by the end of the period will be unemployed at the start of the next period.

There are three general types of searchers: the unemployed, the employed, and the recently separated. We first consider the unemployed. 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

$$\bar{u}_t = 1 - \bar{n}_t - \bar{b}_t. \tag{7}$$

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

The second type of searchers we consider are those who search on the job. Absent other considerations, the only reason for an employed worker to search is to find a job with improved match quality.[12] In our setting, the only workers who can improve match quality are those currently in bad matches. We allow such workers to search with variable intensity ς_{bt}. As has been noted in the literature, however, not all job transitions involve positive wage changes (see Flinn, 2002). Accordingly, we suppose that workers in good matches may occasionally leave for idiosyncratic reasons, e.g. locational constraints.[13] We assume that these workers search with fixed intensity ς_n and only accept other good matches.[14]

Finally, we assume that the fraction $1-\nu$ of workers separated during period t search with fixed intensity ς_u. Such workers are either hired by another firm to work in the subsequent period or remain unemployed. As is the case with workers searching from unemployment, workers separated within the period will find it optimal to both accept good or bad matches. We include such flows to be consistent with the observation that workers observed making job-to-job transitions sometimes are observed to take pay cuts; and, as pointed out by Christiano, Eichenbaum, and Trabandt (2013), flows in the data that appear to be job-to-job transitions

[12] Strictly speaking, with staggered wage contracting, workers in good matches may want to search if their wages are (i) sufficiently below the norm and are (ii) not likely to be regotiated for some time. However, because the fraction of workers likely to be in this situation in our model is of trivial quantitative importance, due to the transitory nature on average of wage differentials due to staggered contracting, we abstract from this consideration.

[13] 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 et al. (2006) and Lentz and Mortensen (2012).

[14] Note that as the expected gains from search for such workers is zero up to a first order, there is no loss of generality in assuming fixed search intensity.

may in fact be separations immediately followed by successful job search. We assume $\varsigma_u < 1$, consistent with the notion in the search literature that, for various reasons, employed workers search with less efficiency than unemployed workers (e.g., employed workers have less time to devote to search than unemployed workers).

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

$$\bar{s}_t = \bar{u}_t + \nu(\varsigma_{bt}\bar{b}_t + \varsigma_n\bar{n}_t) + (1-\nu)\varsigma_u(\bar{n}_t + \bar{b}_t) \tag{8}$$

The first term reflects search intensity of the unemployed; the second term, the search intensity of the employed; the third, the search intensity of workers separated within the period. 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:

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

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

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

$$p_t = \frac{\bar{m}_t}{\bar{s}_t} \tag{10}$$

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

$$\begin{aligned} p_t^n &= \xi p_t \\ p_t^b &= (1-\xi)p_t \end{aligned} \tag{11}$$

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

$$q_t^m = \frac{\bar{m}_t}{\bar{v}_t} \tag{12}$$

Not all matches lead to hires, however, and hires vary by quality. The probability q_t^n a vacancy leads to a good quality hire and the probability q_t^b it leads to a bad quality one are given by

$$q_t^n = \xi q_t^m \tag{13}$$
$$q_t^b = (1-\xi)\left(1 - \frac{\nu(\varsigma_{bt}\bar{b}_t + \varsigma_n \bar{n}_t)}{\bar{s}_t}\right) q_t^m \tag{14}$$

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, ξ, and the probability of a match, q_t^m. By contrast, since on the job searchers do not accept bad matches, to compute q_t^b we must net out the fraction of searchers who are doing so on the job, $\nu(\varsigma_{bt}\bar{b}_t + \varsigma_n \bar{n}_t)/\bar{s}_t$.

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

$$q_t = q_t^n + \phi q_t^b \tag{15}$$

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

3.2 Firms

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

$$y_t = z_t k_t^{\alpha} l_t^{1-\alpha}, \tag{16}$$

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 (6)). 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:

$$l_t = n_t + \phi b_t = (1 + \phi\gamma_t)n_t, \tag{17}$$

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

The evolution of l_t depends on the dynamics of both n_t and b_t. Let ρ_t^i be the probability of retaining a worker in a match of type $i = n, b$. Letting q_t^i denote the probability of filling a vacancy with a worker leading to a match of type i, we can express the evolution of n_t and b_t

as follows:

$$
\begin{aligned}
n_{t+1} &= \rho_t^n n_t + q_t^n \upsilon_t && (18)\\
b_{t+1} &= \rho_t^b b_t + q_t^b \upsilon_t && (19)
\end{aligned}
$$

where $q_t^i \upsilon_t$ is the quantity of type i matches and where equation (13) defines q_t^n and q_t^b. The probability of retaining a worker is the product of the job survival probability ν and the probability the worker does not leave for a job elsewhere $(1 - \varsigma_{it} p_t^n)$:

$$
\rho_t^i = \nu(1 - \varsigma_{it} p_t^n),\ \ i = n, b, \tag{20}
$$

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

$$
\rho_t = \frac{\rho_t^n + \phi \gamma_t \rho^b}{1 + \phi \gamma_t} \tag{21}
$$

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

$$
x_t = \frac{q_t \upsilon_t}{l_t} \tag{22}
$$

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:

$$
l_{t+1} = (\rho_t + x_t)\, l_t \tag{23}
$$

Next, we can make use of equations (17), (18), (19) and (22) to characterize how the quality mix of workers $\gamma_t = b_t/n_t$ evolves over time:

$$
\begin{aligned}
\gamma_{t+1} &= \frac{\rho_t^b \gamma_t + q_t^b \upsilon_t / n_t}{\rho_t^n + q_t^n \upsilon_t / n_t} && (24)\\
&= \frac{\rho_t^b \gamma_t + \frac{q_t^b}{q_t}(1 + \phi \gamma_t) x_t}{\rho_t^n + \frac{q_t^n}{q_t}(1 + \phi \gamma_t) x_t}
\end{aligned}
$$

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 homogenous in the existing stock l_t.[15] Then

[15] We assume quadratic recruiting costs because we have temporary wage dispersion due to staggered contracts

let $\Lambda_{t,t+1}$ be the firm's stochastic discount factor, i.e. the household's intertemporal marginal rate of substitution, r_t the rental rate, and the wage per efficiency unit of labor, w_t. 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 γ_t, and given the expected paths of rents and wages. In particular, we may express the value of each firm $F(l_t, \gamma_t, w_t, \mathbf{s}_t) \equiv F_t$ as

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

subject to equations (23) and (24), and given the values of the firm level states (l_t, γ_t, w_t) and the aggregate state vector $\mathbf{s}_t$. 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

$$F_t = J_t \cdot l_t \tag{25}$$

with $J_t \equiv J(\gamma_t, w_t, \mathbf{s}_t)$ given by

$$J_t = \max_{\check{k}_t, x_t} \{ z \check{k}_t^{\alpha} - \frac{\kappa}{2} x_t^2 - w_t - r_t \check{k}_t + (\rho_t + x_t) \mathbb{E}_t \{ \Lambda_{t,t+1} J_{t+1} \} \}. \tag{26}$$

subject to (23) and (24).

The first order condition for capital rental is

$$r_t = \alpha z_t \check{k}_t^{\alpha - 1}. \tag{27}$$

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

The first order condition for hiring is

$$\kappa x_t = \mathbb{E}_t \left\{ \Lambda_{t,t+1} \left[J_{t+1} + (\rho_t + x_t) \frac{\partial J_{t+1}}{\partial \gamma_{t+1}} \frac{\partial \gamma_{t+1}}{\partial x_t} \right] \right\} \tag{28}$$

The expression on the left is the marginal cost of adding worker, while the one on the right is

and perfectly mobile capital. With proportional costs, all capital would flow to the low wage firms.

discounted marginal benefit. The first term on the right-hand side of (28) 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 in the value of a unit of labor quality to the firm.[16]

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 value of unemployment, which we take to be unemployment benefits. Then, the value of a worker in unemployment satisfies

$$U_t = u_b + \mathbb{E}_t \left\{ \Lambda_{t,t+1} \left[p_t^n \bar{V}_{t+1}^n + p_t^b \bar{V}_{t+1}^b + (1 - p_t) U_{t+1} \right] \right\}. \tag{29}$$

where the unconditional job finding probability p_t, and the probabilities of finding good and bad matches, p_t^n and p_t^b, are given by equations (10) and (11), and where $\bar{V}_{t+1}^n$ and $\bar{V}_{t+1}^b$ are the average values of good and bad matches at time $t+1$.[17]

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

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

where $i = b, n, u$. Let w_{it} be the wage of a type i worker, $i = n, b$. The value of a worker in a

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

[17] 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 $\bar{V}_{t+1}^i = \int V_{t+1}^i dG_{t+1}$, where G denotes the joint distribution of wages and composition, while the average value conditional on being a new hire is given by $\bar{V}_{x,t+1}^i = \int V_{t+1}^i (x_t/\bar{x}_t) dG_t$, where $\bar{x}_t = \int x_t dG_t$. Since w, γ 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.

bad match is given by

$$
\begin{aligned}
V_t^b &= \max_{\varsigma_{bt}}\{w_{bt} + \tau_t - [\nu c(\varsigma_{bt}) + (1-\nu)c(\varsigma_u)] \\
&\quad + \mathbb{E}_t\{\Lambda_{t,t+1}\{\nu[(1-\varsigma_{bt}p_t^n)V_{t+1}^b + \varsigma_{bt}p_t^n\bar{V}_{t+1}^n] \\
&\quad + (1-\nu)[\varsigma_u p_t^n \bar{V}_{t+1}^n + \varsigma_u p_t^b \bar{V}_{t+1}^b + (1-\varsigma_u p_{t+1})U_{t+1}]\}\}
\end{aligned}
\tag{30}
$$

The flow value is the wage w_{bt} net the expected costs of search plus a term τ_t we describe below. If the worker "survives" within the firm, which occurs with probability ν, he searches with variable intensity ς_{bt}. If he is separated, which occurs with probability $1-\nu$, he searches with fixed intensity ς_u. 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 third term and fourth term reflect the value of being separated but immediately finding a good or bad job. The final term reflects the value of being separated into unemployment.

A worker in the bad match chooses the optimal search intensity ς_{bt} according to (30), satisfying

$$
\varsigma_0 \varsigma_{bt}^{\eta_\varsigma} = \mathbb{E}_t\left\{\Lambda_{t,t+1}p_t^n\left(\bar{V}_{t+1}^n - V_{t+1}^b\right)\right\}
\tag{31}
$$

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 (31) 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.

If there is dispersion of wages among bad matches due staggered contracting, then search intensities can differ across these workers. To simplify matters, we assume that the family provides an insurance scheme that smooths out search intensities across its family members, much in the same way it offers consumption insurance. In particular, we assume that there is a transfer scheme that insures that the sum of the wage and the transfer equals the average wage across matches, $\bar{w}_{bt}$. In particular, $\tau_t = (\bar{w}_{bt} - w_{bt})$, which implies $w_{bt} + \tau_t = \bar{w}_{bt}$. With the transfer, the discounted marginal benefit to search (the right side of equation (31)) does not depend on worker-specific characteristics, so that $V_t^b = \bar{V}_t^b$. Search intensity is thus the same across all workers in bad matches.

The value of a worker in a good match is analogous to the value function for a bad match.

$$\begin{aligned} V_t^n &= w_{nt} - [\nu c(\varsigma_n) + (1-\nu)c(\varsigma_u)] \\ &\quad +\mathbb{E}_t\{\Lambda_{t,t+1}\{\nu[(1-\varsigma_n p_t^n)\bar{V}_{t+1}^b + \varsigma_n p_t^n V_{t+1}^n] \\ &\quad +(1-\nu)[\varsigma_u p_t^n \bar{V}_{t+1}^n + \varsigma_u p_t^b \bar{V}_{t+1}^b + (1-\varsigma_u p_{t+1})U_{t+1}]\}\} \end{aligned} \tag{32}$$

One key difference is that on-the-job search intensity is fixed for good matches. Note that up to a first order, however, there are zero expected gains from search given that workers in good matches only move to other good matches. Hence, we rule out variable search by workers in good matches without loss of generality.

For technical simplicity, we suppose that the search intensities of good and bad workers are identical in steady state (i.e., $\varsigma_{bt} = \varsigma_n$ in steady state). This will imply that in the steady state, good and bad matches will have the same level of expected longevity a firm, which will in turn help simplify the impact of the distribution of workers between good and bad matches on the equilibrium (in the first order approximation).

3.4 Nash Wage

As in GT, workers and firms divide the joint match surplus via staggered Nash bargaining. For simplicity, we assume that the firm bargains with good workers for a wage. Bad workers then receive the fraction ϕ of the wage for good workers, corresponding to their relative productivity. Thus if w_t is the wage for a good match within the firm, then ϕw_t is the wage for a bad match. It follows that w_t corresponds to the wage per unit of labor quality. We note that this simple rule for determining wages for workers in bad matches approximates the optimum that would come from direct bargaining. 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 (26)). For good workers, the relevant surplus is the difference between the value of a good match and unemployment:

$$H_t = V_t^n - U_t \tag{33}$$

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

Let w_t^* denote the wage per unit of labor quality of a firm renegotiating its wage contract in the current period.[18] The wage w_t^* is chosen to maximize the joint Nash product of a unit of labor quality to a firm and a worker in a good match, given by

$$H_t^{\eta} J_t^{1-\eta} \tag{34}$$

subject to

$$w_{t+1} = \begin{cases} w \text{ with probability } \lambda \\ w_{t+1}^* \text{ with probability } 1-\lambda \end{cases} \tag{35}$$

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

Let $H_t^* \equiv H(\gamma_t, w_t^*, \mathbf{s}_t)$ and $J_t^* \equiv J(\gamma_t, w_t^*, \mathbf{s}_t)$ (where $H_t \equiv H(\gamma_t, w_t, \mathbf{s}_t)$ and $J_t \equiv J(\gamma_t, w_t, \mathbf{s}_t)$). Then the first order condition for w_t^* is given by

$$\eta \frac{\partial H_t^*}{\partial w_t^*} J_t^* = (1-\eta)\left(-\frac{\partial J_t^*}{\partial w_t^*}\right) H_t^* \tag{36}$$

where

$$\frac{\partial H_t^*}{\partial w_t^*} = 1 + \nu\left(1 - \varsigma_n p_t^n\right) \mathbb{E}_t \left\{\Lambda_{t,t+1}\left[\lambda \frac{\partial H_{t+1}}{\partial w_t^*} + (1-\lambda)\frac{\partial H_{t+1}^*}{\partial w_t^*}\right]\right\} \tag{37}$$

and

$$\frac{\partial J_t^*}{\partial w_t^*} = 1 + (\rho_t + x_t)\mathbb{E}_t \left\{\Lambda_{t,t+1}\left[\lambda \frac{\partial J_{t+1}}{\partial w_t^*} + (1-\lambda)\frac{\partial J_{t+1}^*}{\partial w_t^*}\right]\right\}.$$

Under multi–period bargaining, the outcome depends on how the new wage settlement affects the relative surpluses 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

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

contract remains operative, λ^i. We derive this expression for this model in the appendix.

In general, the new contract wage will be a function of the firm level state γ_t (the ratio of bad to good matches), as well as the aggregate state vector $\mathbf{s}_t$. However, given our assumptions that steady state search intensities are the same for good and bad matches and that wages are proportional to productivity, w_t^* is independent of γ_t in the first order approximation. Accordingly, to a first order, we can express the evolution of average wages $\overline{w}$ as

$$\overline{w}_t = (1-\lambda)w_t^* + \lambda\overline{w}_{t-1}$$

where

$$\overline{w}_t =$$

where $1-\lambda$ is the fraction of firms that are renegotiating and λ is the fraction that are not. (See the appendix for details.)

3.5 Households: Consumption and Saving

We adopt the representative family construct, following Merz and Andolfatto, which essentially generates perfect consumption insurance. There is a measure of families on the unit interval, each with a measure one of workers. The distribution of unemployed and employed workers (along with their wages) within the family is that of the aggregate distribution. 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 $\overline{k}_t$, which is rented to firms at rate r_t and depreciates at the rate δ.

Let $\Omega_t \equiv \Omega(\mathbf{s}_t)$ be the value of the representative household. Then,

$$\Omega_t = \max_{\bar{c}_t,\bar{k}_{t+1}} \{\log(\bar{c}_t) + \beta\mathbb{E}_t\Omega_{t+1}\} \tag{38}$$

subject to

$$\bar{c}_t + \overline{k}_{t+1} - \frac{\varsigma_0}{1+\eta_\varsigma}\left\{\left[\nu\varsigma_n^{1+\eta_\varsigma} + (1-\nu)\varsigma_u^{1+\eta_\varsigma}\right]\bar{n}_t + \left[\nu\varsigma_{bt}^{1+\eta_\varsigma} + (1-\nu)\varsigma_u^{1+\eta_\varsigma}\right]\bar{b}_t\right\}$$
$$= \bar{w}_t\bar{n}_t + \phi\bar{w}_t\bar{b}_t + (1-\bar{n}_t-\bar{b}_t)u_b + (1-\delta+r_t)\overline{k}_t + T_t + \Pi_t, \tag{39}$$

and

$$\bar{n}_{t+1} = \bar{\rho}_t^n \bar{n}_t + q_t^n \bar{\upsilon}_t \tag{40}$$

$$\bar{b}_{t+1} = \bar{\rho}_t^b \bar{b}_t + q_t^b \bar{\upsilon}_t \tag{41}$$

where Π_t are the profits from the household's ownership holdings in firms and T_t are lump sum transfers from the government.

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

$$1 = (1 - \delta + r)\mathbb{E}_t\{\Lambda_{t,t+1}\} \tag{42}$$

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:

$$\begin{aligned} \bar{y}_t = \bar{c}_t + \bar{k}_{t+1} - (1-\delta)\bar{k}_t \\ + \frac{\kappa}{2} \int_i x_t^2 l_t di + \frac{\varsigma_0}{1+\eta_\varsigma} \left(\left[\nu \varsigma_n^{1+\eta_\varsigma} + (1-\nu) \varsigma_u^{1+\eta_\varsigma} \right] \bar{n}_t + \left[\nu \varsigma_{bt}^{1+\eta_\varsigma} + (1-\nu) \varsigma_u^{1+\eta_\varsigma} \right] \bar{b}_t \right). \end{aligned} \tag{43}$$

The government funds unemployment benefits through lump-sum transfers:

$$T_t + \left(1 - \bar{n}_t - \bar{b}_t\right) u_b = 0. \tag{44}$$

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's period wage rate w_{t+1}; (v) the search intensity of a worker in a bad match ς_{bt};(vi) the rental rate on capital r_t; (vii) the average wage and hiring rates, $\bar{w}_t$ and $\bar{x}_t$; (viii) the capital labor ratio $\check{k}_t$; (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; and (xii) a transition function $Q_{t,t+1}$. The solution is such that (i) w_t^* satisfies the Nash bargaining condition (36); (ii) x_t satisfies the hiring condition (28); (iii) w_{t+1} is given by the Calvo process for wages (35); (iv) ς_{bt} satisfies the first-order condition for search intensity of workers in bad matches (31); (v) r_t satisfies (27); (vi) $\bar{w}_t = \int w_t dG_t$ and $\bar{x}_t = \int x_t dG_t$; (vii) the rental market for capital clears,

$\check{k}_t = \bar{k}_t / \left(\bar{n}_t + \phi \bar{b}_t\right)$; (viii) $\bar{c}_t$ and $\bar{k}_{t+1}$ solve the household problem (38); (ix) $\bar{n}_t(\mathbf{s}_t)$ and $\bar{b}_t(\mathbf{s}_t)$ evolve according to (40) and (41); (x) the evolution of G_t is consistent with $Q_{t,t+1}$; (xi) $Q_{t,t+1}$ is defined in equation (xx) 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).

Let $\bar{g}_t^w$ denote the average wage growth of continuing workers, $\bar{g}_t^{JC}$ the average wage growth of new hires who are job changers, and $\bar{c}_t^w$ the component of $\bar{g}_t^{JC}$ 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:

$$\widehat{\bar{g}}_t^{JC} = (1-\omega)\widehat{\bar{g}}_t^w + \omega \widehat{\bar{c}}_t^w \tag{45}$$

with

$$\widehat{\bar{g}}_t^w = \widehat{\bar{w}}_t - \widehat{\bar{w}}_{t-1} \tag{46}$$

$$\widehat{\bar{c}}_t^w = \pi_1 \widehat{\delta}_{BG,t-1} - \pi_2 \widehat{\delta}_{GB,t-1} \tag{47}$$

where $\widehat{z}$ denotes log deviations of variable z 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 ω, π_1, and π_2 are all positive and are functions of model primitives.

Equation (45) 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 $\widehat{\bar{c}}_t^w$ varies positively with share in total job flows of workers moving from bad to good matches $\widehat{\delta}_{BG,t-1}$ and negatively with the share movement from good to bad $\widehat{\delta}_{GB,t-1}$. As we have discussed, the search intensity by workers in bad matches is highly procyclical, leading to $\widehat{\delta}_{BG,t-1}$ being procyclical and $\widehat{\delta}_{GB,t-1}$ countercyclical. The net effect is that $\widehat{c}_t^w$ 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 cyclicality 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 cyclicality as for existing workers.

Note also that the model features no match quality effect for workers searching from unemployment, as workers from unemployment accept good and bad matches alike. This is consistent with the estimates from the previous section, which show that new hires coming from unemployment have the same wage cyclicality as continuing workers, even without adding a person-job fixed effect to control for cyclical movements in match quality.

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 cyclicality 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 10 of the parameters using external sources. Five of the externally calibrated parameters are common to the macroeconomics literature: the discount factor, β; the capital depreciation rate, δ; the share of labor in the production technology, α; and the autoregressive parameter and standard deviation for the productivity process, ρ_z and σ_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 $\sigma_z = 0.0075$.

Five more parameters are specific to the search literature. Our choice of the matching function elasticity with respect to searchers, σ, is 0.4, guided by the estimates from Blanchard and Diamond (1989).[19] We set the worker's bargaining power η to 0.5, as in GT. We normalize

[19] This value lays slightly outside the range of values identified by Pissarides and Petrongolo (2001) and well below the value estimated by Shimer (2005). Note that in these papers, only the unemployed search and enter the matching function, while searchers in our model comprise both unemployed and employed workers. When we simulate data from our model and estimate the matching function elasticity under the assumption that only the unemployed search, we recover an elasticity in excess of 0.6.

the matching function constant, σ_m, to 1.0. We set the elasticity of search costs, η_σ, to 1.0. This is close to the value estimated from Danish data by Christensen et al. (2005), 1.19. We choose λ to target the average frequency of wage changes. Taylor (1999) argues that medium to large-size firms adjust wages roughly once every year; this is validated by findings from microdata by Gottschalk (2005), who concludes that wages are adjusted roughly every year. To be conservative, we set $\lambda = 8/9$, implying that wages are renegotiated on average every 3 quarters, which is consistent with the estimates in Gertler, Sala and Trigari (2009). We consider an alternative calibration with $\lambda = 11/12$, implying an average duration between negotiations of one year. The parameter values are given in Table 4.

The remaining six parameters are jointly calibrated to match model-relevant moments measuring aggregate labor flows, individual-level wage dynamics, and the value of leisure. We calibrate the inverse productivity premium, ϕ; the probability that a new match is good, ξ; the hiring cost parameter, κ; the scale parameter of the search cost, ς_0; the flow value of unemployment, u_b; and the separation probability, $(1-\nu)$ to match six moments: the average wage change of workers making E-E transitions in our data; the fraction of job changers who do not experience a change in match quality; the U-E probability; the E-E probability; the relative value of non-work; and the E-U probability. Although there is not a one-to-one mapping of parameters to moments, there is a sense in which the identification of particular parameters are more informed by certain moments than others. We use this informal mapping to provide a heuristic argument of how the various parameters are identified.

We calibrate ϕ to target the average wage change of workers making direct job-to-job transitions in our data, 3.71%; holding everything constant, a higher ϕ implies a smaller (positive) average percentage wage increase for job changers. We recover $\phi = 0.89$. In calibrating ξ, we note that a higher probability of finding a good match from unemployment implies a lower stock of bad workers, and thus fewer bad-to-good job transitions as a fraction of total transitions. Hence, a higher ξ correlates with an economy where a greater proportion of job-changes do not involve a change in match quality. We thus calibrate ξ to match the fraction of E-E transitions in the data that involve no change in match quality. In the model simulated data, we can infer whether a job change involves a switch in match quality by whether the absolute value of the percentage change in wages is greater than $|\log\phi|$. We apply the same standard to the actual data to infer the percentage of job transitions that do not involve a change in match quality. We recover a value of ξ equal to 0.085.

We calibrate the separation probability $(1-\nu)$ to match the empirical E-U probability of 0.026. Note that separated workers have the opportunity to find a new job and avoid unemployment. Hence, the E-U in the model equals $(1-\nu)(1-\varsigma_u\tilde{p})$, implying $(1-\nu)=0.03$ (where $\tilde{z}$ denotes steady state of a variable z). The hiring cost parameter, κ, determines the resources that firms place into recruiting, and hence, influences the probability that a worker finds a job. We set the steady state job finding probability $\tilde{p}$ to match the monthly U-E transition probability, 0.45; and then calibrate κ to be consistent with $\tilde{p}$. We restrict $\varsigma_u=\varsigma_n=\tilde{\varsigma}_b$ and note that a higher search cost implies a a lower E-E flow. We calibrate ς_i to match an E-E flow of 0.029; we obtain $\varsigma_0=0.12$, implying $\varsigma_i=0.55$.

We calibrate the flow value of unemployment u_b to be consistent with Hall and Milgrom (2008), who estimate the relative value of nonwork to work activities $\bar{u}_T$ to be 0.71. In our setting, the relative value of nonwork activities satisfies

$$\bar{u}_T=\frac{u_b+\frac{\varsigma_0}{1+\eta_\varsigma}\left[\nu\tilde{\varsigma}^{1+\eta_\varsigma}+(1-\nu)\varsigma_u^{1+\eta_\varsigma}\right]}{\tilde{a}+(\kappa/2)\tilde{x}^2}.$$

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. The full list of parameter values and targeted moments are given in Table 5.

Finally, when taking the model to the data, we assume that workers employed in bad matches enjoy an additional benefit equal to $(1-\phi)u_b$. Since workers in bad matches receive a fraction ϕ of the wage paid on average to good workers, they should be entitled to a fraction ϕ of the unemployment benefit u_b in case of separation, for given replacement rate. To avoid making the value of unemployment dependent on the type of match the unemployed worker separated from, we achieve the same goal by adding to the wage ϕw the benefit $(1-\phi)u_b$. This way, the period surplus from employment in a bad match becomes proportional to the period surplus in a good match: $\phi w+(1-\phi)u_b-u_b=\phi\,(w-u_b)$.

Having fully calibrated the model, we now evaluate whether it provides an accurate description of aggregate and individual-level dynamics. We first test the ability of the model to match the cyclical properties of aggregate unemployment and wages. Second, we assess the ability of the model to generate the correct relative 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 the how the model works to capture the aggregate data, we first compute impulse responses to a one percent shock to productivity. 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. The model with wage rigidity produced 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 job-to-job transitions. We see that the addition of job-to-job transitions does not alter the main implications of wage rigidity for aggregate dynamics.

We begin by computing a variety of business cycle moments obtained from stochastic simulation obtained from feeding in a random sequence of productivity shocks. We do not mean to suggest that productivity shocks are the main business cycle driving forces. Rather, the simple real business cycle model offers a convenient way of studying the model implications for unemployment and wage dynamics.

We first consider the model implications of an impulse response to a one percent increase in productivity. The plots are given in Figure 2. To highlight the role of staggered contracting, we plot the model generated output for the benchmark case ($\lambda = 8/9$) and the flexible wage case ($\lambda = 0$). 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 by very little. In the case with staggered contracting, the pattern is reversed: wages adjust gradually and only modestly, whereas there are large and immediate changes in employment, unemployment, and vacancies. We also find a greater increase in 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 far 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 panel computes the same statistics using the model. Here we use our baseline assumption that wage contracts have an expected duration of three quarters.

Overall the model does a reasonable job of accounting for the relative volatility of unemployment (5.60 in the model versus 5.74 in the data) and for wages (0.37 versus 0.48). As is common in the literature, the model understates the volatility of employment and overstates the volatility of vacancies. In the former case, the absence of a labor force participation margin is relevant and in the latter, error in measuring vacancies 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. Though we do not report the results here, the model vastly understates unemployment volatility under period-by-period Nash bargaining.

We next turn to the model's ability to account for the panel data evidence. We use a stochastic simulation of the model to generate a time series on the unemployment rates and on the wages of new hires versus continuing workers. We then estimate equation (1) using the simulated data. Table 7 compares the results from the panel data (the first column) with those obtained from data from our baseline model (the second column). Note that the estimates of cyclical wage elasticities for continuing versus new workers are very similar in both cases. The model is thus able to produce estimates suggesting relatively greater cyclicality of new hires' wages in a magnitude consistent with the evidence. The estimated excess cyclicality, however, is clearly an artifact of composition bias: After controlling for match quality, new hires' wages in the model are exactly as cyclical as they are for continuing workers.

Our baseline model has wage contracts fixed for three quarters on average. In the last column we explore the implications of having period-by-period Nash bargaining for wage determination. While the new hire effect remains, the estimated wage elasticities are too large by a factor of ten. 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.

Figures 3 and 4 illustrates how compositional effects influence wage dynamics. We repeat the experiment of a one percent increase in TFP. Figure 3 then reports impulse responses for labor in efficiency units, good matches, bad matches and job flows between good and bad matches. In the wake of the boom, labor quality increases. Underlying this increase is a rise in good matches and a net fall in bad matches. The rise in good matches is in part due 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.[20]

Figure 4 the decomposes the response of new hires' wage growth into the part due to the growth of contracts wages and the part due to compositional effects, using equations (45), (46), and (47). The sold line in the top panel is total new hires' wage growth, the dashed line is the part due to composition, and the dashed line is average contract wage growth. As the figure illustrates, most of the new hires' wage response 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.

Finally, while our motivation for introducing procyclical job reallocation is to account for the panel data evidence, we note that it also generates interesting implications for the cyclical behavior of productivity. In particular, total factor productivity in the model depends on the allocation of workers between good and bad matches. To see this, we take the production function (16) and the definition of labor quality (17) to obtain an expression for how productivity depends on the quality composition, measured by $\gamma_t = b_t/n_t$:

$$\begin{aligned} y_t &= z_t k_t^{\alpha} \left(n_t + \phi b_t\right)^{1-\alpha} \\ &= z_t \left(\frac{1+\phi\gamma_t}{1+\gamma_t}\right)^{1-\alpha} k_t^{\alpha}(n_t + b_t)^{1-\alpha} \end{aligned}$$

where the term $z_t \left(\frac{1+\phi\gamma_t}{1+\gamma_t}\right)^{1-\alpha}$ is the effective level of TFP. Loglinearizing this term yields the effect of cyclical reallocation on cyclical productivity:

$$\widehat{z}_t - (1-\alpha)\frac{1}{1+\gamma}\frac{1-\phi}{1+\phi\gamma}\widehat{\gamma}_t$$

Since $\widehat{\gamma}_t$ is countercyclical, the effect of labor reallocation on productivity is procyclical.

In Figure 6 we report the response of the endogenous component of productivity e_t to a one

[20] In gross term there are bad matches due to workers being hired from unemployment. The behavior of the job to job flows swamps this effect however.

percent increase in the exogenous component z_t, where $\widehat{e}_t$ can be expressed as

$$\widehat{e}_t = -(1-\alpha)\frac{1}{1+\gamma}\frac{1-\phi}{1+\phi\gamma}\widehat{\gamma}_t.$$

The endogenous component adds a small – roughly 0.13 percent at the peak – but highly persistent effect on productivity, as the top panel suggests. The bottom panel shows the effect on output: the improvement in aggregate match quality due to the reallocation of labor leads to a similarly modest but persistent increase in output. Hence, for this particular experiment, the impact of the endogenous component of TFP on output is relatively modest. Consider a different experiment, however, where output is reduced by the amount it fell during the Great Recession (roughly ten percent relative to trend). A back-of-the-envelope calculation based on Figure 6 would then suggest that the fall in output would be accompanied by a persistent drop in productivity of more than a percentage point due to the endogenous reallocation of labor.

5 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 reinforce this point by developing a model of aggregate unemployment that generates quantitative implications consistent with both macro and micro data. In the model, new hires' wages are the same as continuing workers of the same match productivity; but, as we find in our estimates from panel data, new hire wages appear to be more cyclical due to the procyclicality of job quality in new matches. Our bottom line: it is reasonable for macroeconomists to continue to make use of wage rigidity to account for economic fluctuations. The focus should be on how best to model wage rigidity rather than whether it is appropriate to model at all.

Finally, our model of unemployment fluctuations with staggered wage contracting differs from much of the literature in allowing a channel for procylical job-to-job transitions. For many purposes, it may be fine to abstract from this extra complication. 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. Recent studies by Haltiwanger, Hyatt and McEntarfer (2013) and Moscarini and Postel-Vinay (2014) provide 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. It might be interesting to explore these issues and consider other factors, such as financial market frictions, that have likely hindered the reallocation process in the recent recession.

6 Appendix (to be completed)

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Table 1: "Bils regressions" and the new hire effect

	1990-2012 sample	
	(1)	(2)
Unemployment rate	-0.424^{***}	-0.317^{***}
	(0.0541)	(0.0794)
Unemp. rate $\cdot$ $\mathbb{I}$(new)	-0.870^{***}	-1.248^{***}
	(0.2293)	(0.4368)
Estimator	FE	FD
No. observations	417,404	359,954

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)

	1990-2012 sample		
	(1)	(2)	(3)
UR	-0.429^{***}	-0.431^{***}	-0.431^{***}
	(0.0543)	(0.0545)	(0.0545)
UR $\cdot\ \mathbb{I}$(new & EE)	-1.275^{***}	-1.280^{***}	-1.185^{***}
	(0.3743)	(0.3744)	(0.3310)
UR $\cdot\ \mathbb{I}$(new & ENE)	0.083	-0.212	0.272
	(0.3857)	(0.4664)	(0.6187)
$P(\beta_{U,n}^{EE} = \beta_{U,n}^{ENE})$	0.010	0.070	0.036
Unemp spell for ENE	0+	$(0, 4]$	$(1, 4]$
No. observations	413,395	413,395	413,395
No. of fixed effects	57,010	57,010	57,010

Robust standard errors in parenthesis

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

Table 3: Person-Job Fixed Effects and the New Hire Effect

	1990-2012 sample		
	(1)	(2)	(3)
UR	-0.231^{***}	-0.231^{***}	-0.230^{***}
	(0.0523)	(0.0522)	(0.0524)
UR $\cdot\ \mathbb{I}$(new)	-0.289	–	–
	(0.2620)	–	–
UR $\cdot\ \mathbb{I}$(new & EE)	–	-0.357	-0.358
	–	(0.4945)	(0.4944)
UR $\cdot\ \mathbb{I}$(new & ENE)	–	–	-0.089
	–	–	(0.4014)
No. observations	399,690	396,536	396,536
No. of fixed effects	66,260	65,688	65,688

Robust standard errors in parenthesis

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

Table 4: Calibration

Parameter values		
Discount factor	β	$0.997 = 0.99^{1/3}$
Capital depreciation rate	δ	$0.008 = 0.025/3$
Production function parameter	α	0.33
Technology autoregressive parameter	ρ_z	$0.983 = 0.95^{1/3}$
Technology standard deviation	σ_z	0.0075
Elasticity of matches to searchers	σ	0.4
Bargaining power parameter	η	0.5
Matching function constant	σ_m	1.0
Search cost elasticity	η_ς	1.0
Renegotiation frequency	λ	0.889 (3 quarters)

Table 5: Jointly calibrated parameters

Parameter	Description	Value	Target
ϕ	Inverse productivity premium	0.89	Average E-E wage increase (3.71%)
ξ	Prob. of good match	0.08	Fraction E-E with $\Delta w \approx 0$ (0.47)
κ	Hiring cost parameter	59.17	U-E probability (0.45)
ς_0	Scale parameter or search cost	0.12	E-E probability (0.029)
u_b	Flow value of unemployment	2.59	Relative value, non-work (0.75)
$1 - \nu$	Separation probability	0.03	E-U probability (0.026)

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	0.88	0.94	0.92	0.92
Correlation with y	1.00	0.57	0.79	-0.87	0.91
	Model Economy, $\lambda = 8/9$ (3 quarters)				
Relative St. Dev.	1.00	0.37	0.32	5.60	10.10
Autocorrelation	0.84	0.94	0.84	0.84	0.80
Correlation with y	1.00	0.73	0.81	-0.81	0.94

Table 7: Wage semi-elasticities

Semi-elasticities of wages w/r.t. unemployment

	SIPP	Model, 3Q	Model, flex
Continuing	-0.43	-0.45	-5.52
New hires	-1.70	-1.97	-9.10

Figure 1: Composition bias and new hire wage cyclicality

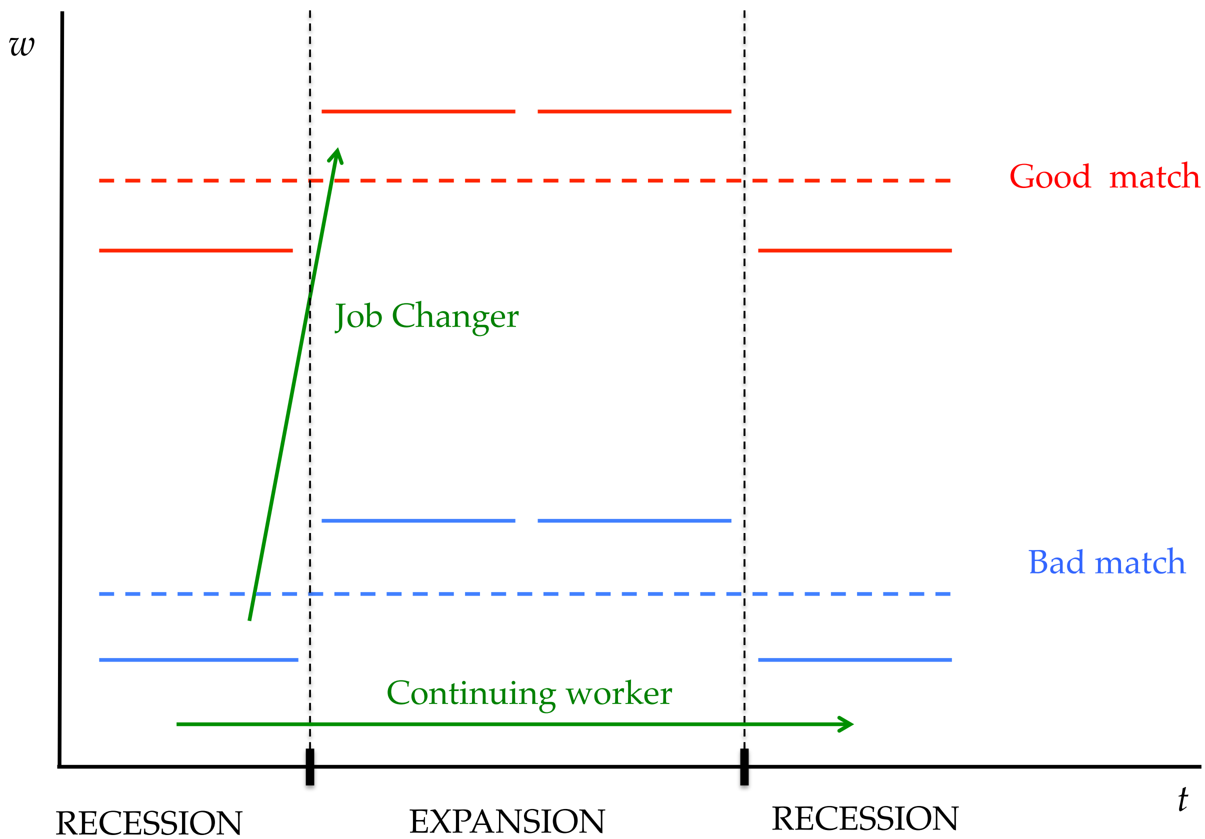

Figure 2: Impulse responses of employment to productivity shock

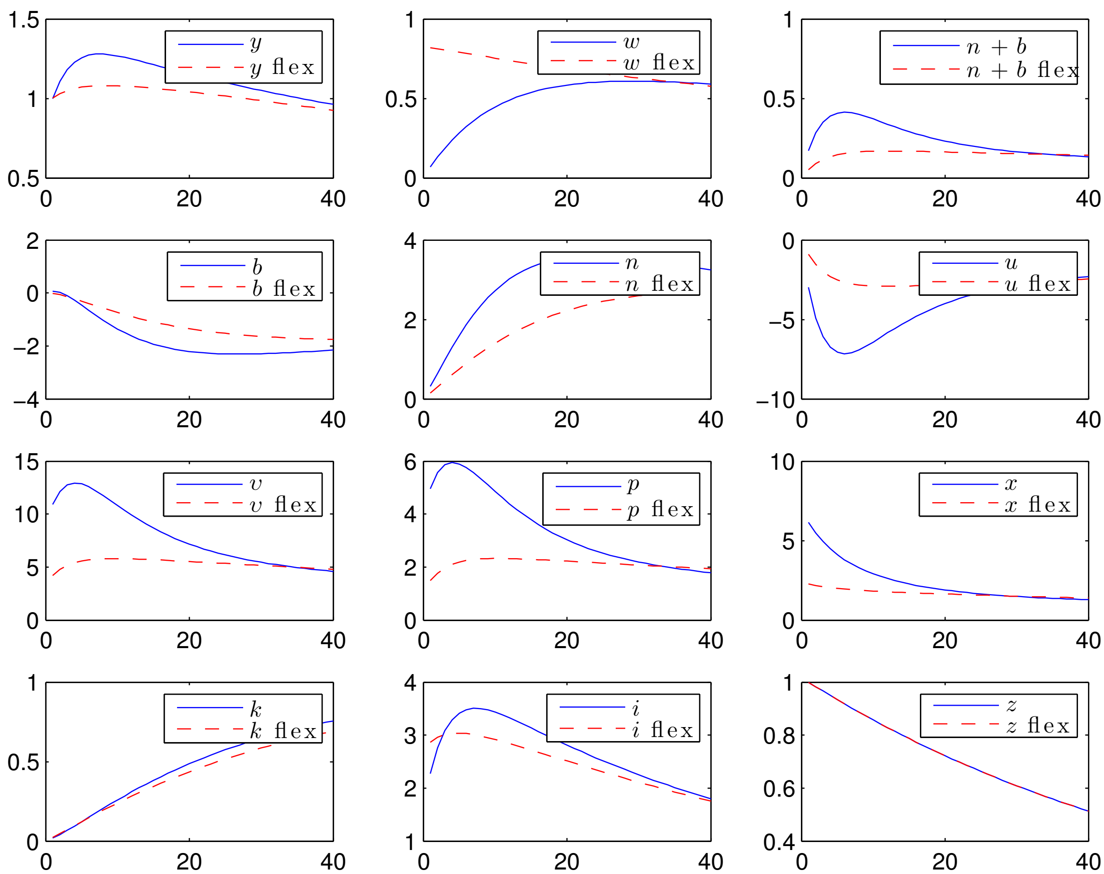

Figure 3: Labor market composition and job flows

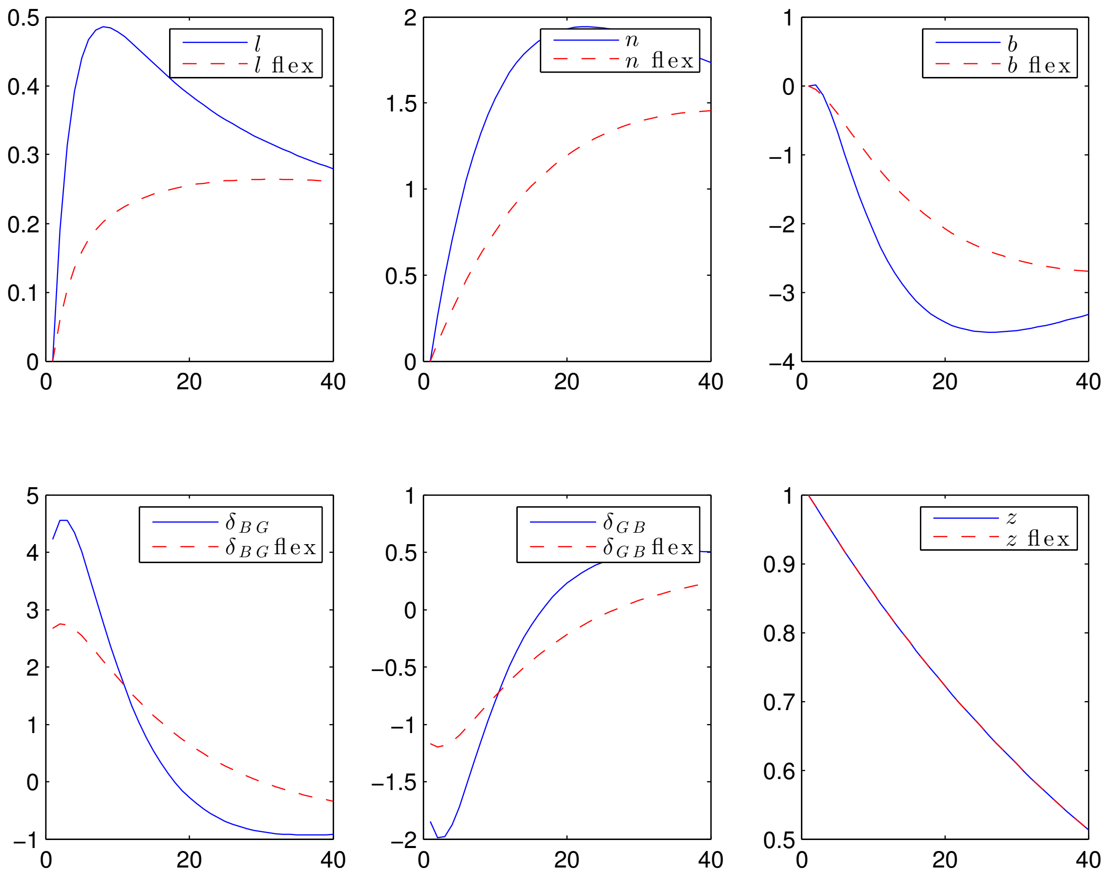

Figure 4: Wage growth and components

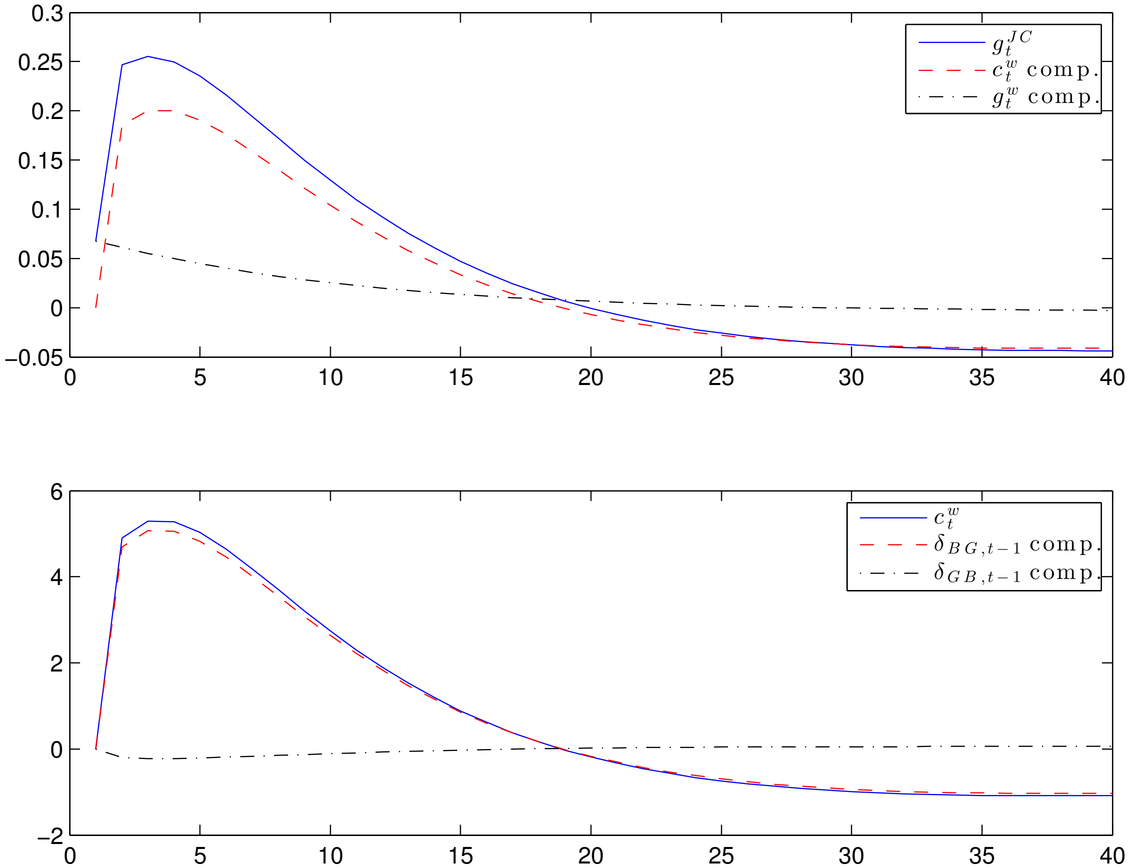

Figure 5: TFP, productivity, and output