Wage Rigidity and Job Creation*

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Preliminary; Comments Welcome

Abstract

Shimer (2005) and Hall (2005) have documented the failure of standard labor market search models to match business cycle fluctuations in employment and unemployment. They argue that it is likely that wages are not adjusted as regularly as suggested by the model, which would explain why employment is more volatile than the model predicts. We explore whether this explanation is consistent with the data. The main insight is that the relevant wage data for the search model are not aggregate wages, but wages of newly hired workers. Our results show that wages for those workers are much more volatile than aggregate wages and respond one-for-one to changes in labor productivity. Thus, we find no evidence for wage rigidity.

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1 Introduction

Shimer (2005) showed that a business cycle version of the search and matching model falls severely short of replicating labor market dynamics. In particular, for reasonable calibrations of the model, the predicted volatility of labor market tightness and unemployment is much lower than observed in the data. Shimer argued that period-by-period Nash bargaining over the wage leads wages to respond strongly to technology shocks, dampening the effect of these shocks on expected profits and therefore on vacancy creation. He suggested wage rigidity as a mechanism worth exploring to amplify the response of vacany creation and unemployment to technology shocks.

Hall (2005) proposed a model of unemployment fluctuations with equilibrium wage stickiness, in which wages are completely rigid when possible and rebargaining takes place only when necessary to avoid match destruction (either through a fire or a quit). In Hall's model there is a unique market wage, which implicitly extends this rigidity of wages on the job to wages of newly hired workers. A large number of more recent papers have appealed to some form of wage rigidity to improve the performance of labor markets models with search frictions to match the business cycle facts in the data (Costain and Reiter 2005; Gertler and Trigari 2006; Blanchard and Galí 2006; Braun 2006).

Few economists would doubt the intuitive appeal of this solution. A simple supply and demand intuition immediately reveals that technology shocks lead to larger fluctuations in the demand for labor if wages are rigid. Furthermore, it is a well documented fact that wages are less volatile than most models of the business cycle predict.[1] Using individual-level panel data on wages, several studies document evidence for wage rigidity in ongoing employment relationships (Bils 1985, Solon, Barsky and Parker 1994, Beaudry and DiNardo 1991).

We argue, however, that the empirically observed form of wage rigidity is not sufficient to generate additional volatility in employment and vacancies. What matters for employment dynamics is not the aggregate wage in the economy, but the wage of the marginal workers that are being hired. Formally, when firms decide on whether or not to post a vacancy, they face a trade-off between the search costs (vacancy posting costs) and the expected net present value of the profits they will make once they find a worker to fill the job. Thus, what matters for this decision is the expected net present

[1] Like the observation that employment (or total hours) are more volatile than predicted by the model, this is true for Real Business Cycle models, search and matching models as well as new Keynesian models.

value of the wage they will have to pay the worker they are about to hire. How this expected net present value is paid out over the duration of the match, is irrelevant (Boldrin and Horvath 1995, Shimer 2004). Of course the net present value of wage payments throughout the employment relationship is not directly observable, but we show that the wage at the time of hiring provides a good proxy for a wide range of models.

In this paper, we present new evidence that wages of newly hired workers are not rigid but respond to productivity shocks as the standard models with flexible wages predict. We construct a quarterly time series for wages of new hires using micro-data on earnings and hours worked from the Current Population Survey (CPS) outgoing rotation groups. We match the outgoing rotation groups to the basic monthly data files in order to construct four months employment history for each individual worker, which allows us to identify new hires at a quarterly frequency. We find that the wage for newly hired workers is much more volatile than the aggregate wage and responds one to one to productivity. We also document that wages for *ongoing* job relationships are indeed rigid over the business cycle. Thus, there is evidence for wage rigidity, but not of the kind that leads to more volatility in employment fluctuations on a labor market with search frictions. We conclude that the failure of the model to match employment fluctuations is related to the job creation process rather than to wage determination.

Beaudry and DiNardo's (1991) model of implicit wage contracts is a good illustration of the type of wage rigidity that we believe to be plausible. Upon the start of a work-relationship the bargaining parties are relatively free in their wage determination. However, once the contract has been signed, wages can no longer be changed very much. This kind of rigidity may be sufficient to make employment more volatile in a Real Business Cycle model, where the representative agent chooses how many hours to work based on the going wage rate. However, it does not lead to amplified unemployment fluctuations if adjustment takes place mostly on the extensive margin.

Previous empirical macroeconomic studies have been concerned with *aggregate* wages (Dunlop 1938, Tarshis 1939, Cooley 1995). If the importance of wages of new hires has been recognized at all, then a careful empirical study has been considered infeasible because of lack of data.[2] This practice has given rise to the conventional wisdom that wages fluctuate less than most models predict and that the data would therefore support modeling

[2] Hall (2005) writes that he does "not believe that this type of wage movement could be detected in aggregate data" (p.51). More specifically, Bewley (1999) claims that "there is little statistical data on the pay of new hires" (p.150).

some form of wage rigidity.

Labor economists who have studied wages at the micro-level have mostly been concerned with wage changes of individual employees. Thus, the analysis has naturally been restricted to wages in *ongoing* employment relationships, which have been found to be strongly rigid. Notable exceptions are Devereux and Hart (2006) and Barlevy (2001) who both study job movers and find their wages to be much more flexible than wages of workers in ongoing jobs. Pissarides (2007) surveys these and other empirical micro-labor studies and, like this paper, concludes that the type of rigid wages found in the data are unlikely to solve the Costain-Reiter-Shimer unemployment volatility puzzle. The main difference between these studies and ours, is that we focus on newly hired workers, i.e. workers coming from non-employment, rather than job-to-job movers, which is the relevant wages series for comparison to standard search models. Because wages of non-employment workers are not observed, we need to use a different estimation procedure, which does not require individual-level panel data. Our procedure has the additional advantage that we can use the CPS, which gives us a much larger number of observations than the earlier studies, which use the PSID or NLSY datasets.

In the next section, we formalize the claim that wages of newly hired workers are the relevant wage series to use when evaluating the predictions of a business cycle model with search frictions on the labor market. Section 3 briefly describes our data and compares the wage series for all workers that we construct from the CPS data to more commonly used measures of aggregate wages. In section 4, we focus on the wage series for new hires and present our results. We focus on the elasticity of wages with respect to productivity shocks and show that the data support the assumption that changes in productivity are exogenous. We also explore various forms of composition bias and link our estimates to existing studies using wages from different data sources. Section 5 concludes with a brief discussion of the implications of our results for the literature on employment fluctuations.

2 Model

To illustrate our point, consider a standard search and matching model with exogenous job destruction and aggregate productivity shocks, similar to Shimer (2005). A continuum of ex-ante identical and risk-neutral workers with mass one can be unemployed, in which case they earn a fixed unemployment benefit (including the value of their leisure) $b > 0$ in each period, or employed, in which case they earn a wage w_t. A continuum of risk-neutral firms can open a vacancy, which costs $k > 0$ per period. If a vacancy and an unemployed worker meet, they form a match, which produces output y_t in each period so that the firm makes positive flow profits $y_t - w_t$. Because production requires only labor and the production function has constant returns to scale, the marginal product of labor equals labor productivity (average output per worker) and is independent of total employment. Therefore, we can assume that each firm hires at most one worker without loss of generality. Labor productivity y_t follows an AR(1) process but is always higher than the unemployment benefit, $y_t > b$ for all t, to avoid periods of zero production.

2.1 Job Creation in the basic stochastic search model

Unemployed workers and vacancies match according to a constant returns to scale matching function. This assumption implies that a vacancy is filled with probability $q(\theta_t)$, which is strictly decreasing in labor market tightness $\theta_t = v_t/u_t$, where v_t is the total number of vacancies in the economy and u_t is the unemployment rate. Each period, an unemployed worker finds a job with probability $\theta_t q(\theta_t)$, which is strictly increasing in θ. Each period matches are exogenously separated with probability $\lambda \in (0,1)$.

The unemployment rate next period equals today's unemployment rate plus flows into minus flow out of unemployment, so the aggregate unemployment rate evolves according to

$$u_{t+1} = u_t + \lambda(1-u_t) - \theta_t q(\theta_t) u_t = \lambda + (1 - \lambda - \theta_t q(\theta_t)) u_t. \tag{1}$$

The assumption of a constant separation rate implies that all fluctuations in unemployment are driven by fluctuations in labor market tightness through vacancy creation. Mortensen and Nagypal (2006) and Pissarides (2007) show how endogenous separations can have an important impact on unemployment fluctuations while not affecting the dynamics of labor market tightness. In our paper we primarily focus on the business cycle dynamics of labor market tightness and hence their result allows us to abstract from endogenous job destruction.

Both firms and workers discount future payments at an exogenous and constant discount rate $r > 0$. Free entry drives the value of a vacancy to zero. Therefore, the value to the firm of having a filled job (J_t) is given by[3]

$$(1+r)J_t = y_t - w_t + (1-\lambda)E_t J_{t+1}. \tag{2}$$

[3] We write the model in discrete time but assume that all payments are made at the end of the period, so that the expressions look similar to the continuous time representation.

The Bellman equation for the value of a vacancy and the free entry condition imply the standard job creation equation, $k = q(\theta_t) E_t J_{t+1}$, which can be solved forward to obtain:

$$\frac{k}{q(\theta_t)} = E_t J_{t+1} = \frac{\bar{y}_t - \bar{w}_t}{r + \lambda} \tag{3}$$

where $\bar{y}_t$ and $\bar{w}_t$ denote the 'permanent' levels of labor productivity and the wage, defined as

$$\bar{x}_t = \frac{r + \lambda}{1 + r} \sum_{\tau=1}^{\infty} \left(\frac{1 - \lambda}{1 + r} \right)^{\tau} E_t x_{t+\tau}. \tag{4}$$

Notice that J_t is just the expected net present value of all future output per worker minus the expected net present value of wage payments to that worker, where the firm uses an effective discount rate of $r + \lambda$ because of potential job destruction.

It is important to notice that this version of the job creation condition has been derived without any assumption neither on wage determination nor on how this present value of wages is paid out over time. This job creation condition (3) holds equally for a model with flexible or rigid wages and will be our departure point for the empirical analysis in section 4.

The intuition for this result is that equilibrium tightness is determined by those firms who have not yet found a worker and are deciding whether or not to post a vacancy. These firms are trading off payment of the search cost k with the expected future profits after hiring a worker. What matters for these profits, is the expected future wage payments to be made to the worker.

2.2 Wage determination: flexible wages

To consider wage determination, some assumptions about workers need to be made. Again, we state the components of a very basic model, e.g. Shimer (2005). The expected net present value of being an employed worker (W_t) and an unemployed worker (U_t) are given by the following two Bellman equations.

$$(1 + r)W_t = w_t + (1 - \lambda)E_t W_{t+1} + \lambda E_t U_{t+1} \tag{5}$$

$$(1 + r)U_t = b + \theta_t q(\theta_t) E_t W_{t+1} + (1 - \theta_t q(\theta_t))E_t U_{t+1} \tag{6}$$

The standard assumption in this literature is that firms and workers engage in Nash bargaining over the wage once they have been matched. This assumption implies that the wage is set such that both firm and worker get a fixed proportion of the expected net present value of total surplus generated by the match.

$$\frac{W_t - U_t}{\beta} = \frac{J_t}{1-\beta} = S_t, \tag{7}$$

where $S_t = J_t + W_t - U_t$ is total match surplus and $\beta \in (0,1)$ is workers' bargaining power.

With this assumption, the solution of the model can be conveniently summarized as a Bellman equation for total match surplus

$$(1+r)\,S_t = y_t - b + (1 - \lambda - \theta_t q\,(\theta_t)\,\beta)\,E_t S_{t+1} \tag{8}$$

which again can be solved forward[4] to obtain the wage curve:

$$\bar{w}_t = (1-\beta)b + \beta\bar{y}_t + \beta k\bar{\theta}_t. \tag{9}$$

Equations (9) and (3) uniquely determine the equilibrium values for $\bar{w}_t$ and θ_t, given productivity.

Combining the wage curve (Eq. 9) with the Job Creation Condition (Eq. 3) we can confirm that the elasticity of the permanent wage with respect to productivity can be expressed by

$$\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}} = \frac{\eta(r+\lambda) + \theta q(\theta)}{\frac{\eta}{\beta}(r+\lambda) + \theta q(\theta)}\frac{\bar{y}}{\bar{w}}. \tag{10}$$

Hence with flexible wages the elasticity of wages with respect to productivity approaches $\bar{y}/\bar{w}$ as worker bargaining power goes to one. On the other hand, it is zero for zero worker bargaining power. Figure 1 illustrates the relationship between the wage elasticity and the worker bargaining power for parameter values consistent with the Shimer (2005) calibration and a Hagedorn-Manovskii type small surplus calibration.

It is important to remember that in models with long term employment relationships, like in this matching model, the period wage is not allocative (Boldrin and Horvath 1995). What is pinned down in the model, however, is the present value of these wage payments over the duration of the match. The path at which wages are paid out over the duration of a match is irrelevant for employment fluctuations as long as they do not violate the worker's and firm's participation constraint.

For this reason we now discuss sluggish wage responses in more detail and introduce the key distinction whether the sluggishness applies to wages in ongoing relationships or to wages of all workers.

[4]The detailed steps are in the appendix.

2.3 Wage rigidity in ongoing jobs

First, consider the case of perfectly rigid wages in ongoing jobs. Otherwise, we maintain all assumption as in section 2.2. In particular, we assume that at the beginning of a match, worker and firm engage in pairwise Nash bargaining over the permanent wage. This is the case analyzed in Shimer (2004). As in that paper, we would need to make a parameter restriction to avoid inefficient match destruction. Shimer assumes that search frictions are large enough and the bargaining power of workers is close enough to 1/2 so that, given the stochastic process for labor productivity, the wage in ongoing matches never hits the bounds of the bargaining set. In other words, search frictions are sufficiently large such that the initially bargained wage keeps both firms and workers happy to continue the match at all points in time. Alternatively, we can assume full commitment on the part of both worker and firm, so that matches never get destroyed endogenously (as in the simple case in Rudanko 2006). Since the model is identical for both assumptions, but the second assumption allows to analyze the model for the full range of parameter values, we opt for the latter.

In this model, the permanent wage is completely unaffected by (perfect) wage rigidity in ongoing jobs. And since only permanent wages matter for employment fluctuations, vacancies, labor market tightness and the unemployment rate all behave exactly the same as in the model with flexible wages. Of course, the aggregate wage, or the cross-sectional average wage of all workers in the economy, is much more rigid than in the flexible wage model because at any point in time, many more workers are in ongoing job relationships than in newly created matches. Therefore, a researcher considering the relative volatility, persistence or cyclicality of the aggregate wages, would conclude that there is substantial wage rigidity. In this model however, the observed rigidity in the aggregate wage is irrelevant if we are interested in the cyclical properties of labor market tightness and (un)employment.[5]

Of course the assumption of perfect commitment is rather stark. In general, when the wage of ongoing relationships is completely rigid, productivity shocks will move the bargaining set sufficiently such that it may be in the interest of either the firm or the worker to dissolve the match, even if this may be inefficient. A natural way to generalize the analysis above is to assume, in the spirit of Hall (2005), that firms and workers renegotiate the

[5]Shimer (2004) reaches the same conclusion, that "the rigidity of wages in old matches does not affect the volatility of unemployment and vacancies" (p. 475).

wage when the perfectly rigid wage hits the bounds of the bargaining set.[6] As a modified version of this model, more along the lines of MacLeod and Malcomson (1993), we can also assume that the wage is kept at the bound of the bargaining set if the rigid wage would lie outside of that bound.[7] The most extreme assumption is certainly the perfect commitment full insurance case and so we simulate it and compare results to the perfectly flexible model in section 2.5. It is key that none of these forms of on-the-job wage rigidity have any effect on labor market tightness because they do not affect the evolution of total match surplus over time. For this reason wage rigidity of this form cannot in any way help solve the unemployment volatility puzzle.

An important empirical implication of on-the-job wage rigidity is a sluggish response of aggregate wages to changes in productivity because only the wages of new hires are responsive to the business cycle whereas the wages of ongoing workers will in some form be insured against such fluctuations. Hence this wage determination implies aggregate wage rigidity and at the same time highly elastic wages for newly hired workers.

While the case of flexible wages for new hires and rigid wages for job stayers is the one consistent with previous empirical findings, e.g. Bils (1985), and more recently Hall (2006), many recent models in the search and matching literature have instead opted for a stronger version of wage rigidity where also the wage of newly hired workers is sluggish in responding to productivity fluctuations.

2.4 Wage rigidity for all workers

How can wage rigidity affect fluctuations in labor market tightness and (un)employment? Shimer (2005) suggests modeling wage rigidity as countercyclical bargaining power of workers. This type of wage rigidity implies that the wage for all workers is rigid. In particular, because rigidity is driven by bargaining power, which is common to all workers, there is a unique

[6] This model is in the spirit of Hall (2005), but has rather different implications. Hall extends the wage rigidity in ongoing jobs to wages in newly formed matches by appealing to a social norm. That way, the rigidity strongly affects permanent wages. As Hall notes, not doing so would destroy his result that wage rigidity is important to match employment fluctuations: "if only post-employment wages were sticky and wages paid out in the first period fluctuated to offset anticipated later wages, the model would deliver much smaller fluctuations in labor market conditions" (p. 56).

[7] Another natural generalization would be to assume that matches are (inefficiently) destroyed when the wage hits either bound of the bargaining set, so that matches break up not only exogenously, but also endogenously because of quits and firings. However, the critique of Barro (1977) and the contribution of Hall (2005) and also Gertler and Trigari (2006) was exactly to avoid such inefficient separations.

market wage that all workers in the economy receive. Therefore also permanent wages are rigid in that model, which affects vacancy creation and employment fluctuation. But is this kind of wage rigidity plausible? Most theoretical reasons that have been put forward to explain why wages are rigid seem to refer mostly to wage rigidity in ongoing job relationships, e.g. union agreements, wage indexation, efficiency wages (Yellen 1984), implicit contract agreements or motivational considerations (Bewley 1989, 1999). The same is true for the empirical evidence for wage rigidity (Bils 1985; Solon, Barsky and Parker 1994; Beaudry and DiNardo 1991). In fact, the few studies that consider job movers, find that the wages for these workers are much less rigid than the average wage (Devereux and Hart 2005; Barlevy 2001).

The implication of wage rigidity for all workers (like countercyclical bargaining power) is a sluggish response of the permanent wage to productivity for both workers in ongoing job relationships as well as for newly hired workers. Clearly, a combination of data for all workers and newly hired workers can indicate which of these three alternative assumptions about wage rigidity is supported by empirical evidence.

2.5 Simulation

Because these more general models can no longer be solved analytically, we simulate them. We assume (as in Shimer 2005), that labor productivity follows an AR(1) type process, bounded below by the flow utility of unemployment.

$$y_t = b + e^{z_t}(1-b) \tag{11}$$

$$z_t = \rho z_{t-1} + \varepsilon_t \tag{12}$$

where productivity shocks are normally distributed, $\varepsilon_t \sim N(0, \sigma^2)$. Our calibration of the model parameters is identical to Shimer (2005). As an alternative we present results for a small surplus calibration in the spirit of Hagedorn and Manovskii (2006). In addition to these two models with instantaneously rebargained wages and constant bargaining power we also simulate the model with countercyclical bargaining power as discussed in section 2.4, which leads to rigidity in the unique market wage, and the model with perfectly rigid wages in ongoing jobs and full commitment for both worker and firm. We simulate the model at a weekly frequency and aggregate to quarterly observations.

In table 1 we confirm that the small surplus calibration and the countercyclical bargaining power wage determination can generate large responses of labor market tightness and unemployment to productivity whereas the on-the-job wage rigidity and the flexible wage, large surplus calibration cannot. We notice that the elasticity of permanent wage to permanent productivity in the latter two cases is close to unity, whereas it is substantially smaller for both cases in which labor market tightness responds strongly.

2.6 Equilibrium Tightness Dynamics

To better understand the simulation results, a few lines of simple algebra confirm that the elasticity $\frac{\mathrm{d}\log\theta}{\mathrm{d}\log\bar{y}}$ of labor market tightness, θ, to permanent productivity, $\bar{y}$ is given by

$$\frac{\mathrm{d}\log\theta}{\mathrm{d}\log\bar{y}} = \frac{1}{\eta}\frac{\bar{y} - \frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}}\bar{w}}{\bar{y} - \bar{w}}. \tag{13}$$

Note that this tightness response is derived purely based on the job creation condition. However, we see immediately how the more sluggish wage response of the small surplus calibration and the model with countercyclical bargaining power can generate the larger tightness responses.

This result is not surprising when we think in terms of supply and demand for labor on a Walrasian labor market without search frictions. Fixing the price of labor (perfectly elastic labor supply), amplifies the response of labor demand to shocks in the labor demand curve because workers cannot absorb part of the demand shocks. Here, the intuition is the same. If wages do not increase in response to an increase in productivity, then profits, which are given by $y_t - w_t$, increase more. Compared to a model with flexible wages, this makes it more attractive for firms to post vacancies when productivity is high and less attractive when productivity is low. And therefore, with rigid wages, tightness will increase more when productivity is high and decrease more when productivity is low.

For wages that are completely unresponsive to changes in productivity (i.e. $\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}} = 0$) the response of tightness is the product of the inverse of the matching elasticity, and the $\frac{\bar{y}}{\bar{y}-\bar{w}}$ ratio. While the first term is exogenous to most models, the second can be made arbitrarily large by bringing wages close to productivity. Clearly this is the intuition why the small surplus calibration of Hagedorn and Manovskii (2006) works. Another interesting — albeit extreme — case to consider is the proportionality of wages and productivity, i.e. $\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}} = 1$. The response of tightness simplifies even further to $\frac{\mathrm{d}\log\bar{y}}{\mathrm{d}\log y}/\eta$ which makes it virtually impossible for the model to replicate tightness dynamics. While proportionality is certainly an extreme assumption, it serves to highlight the tension between the response of tightness to productivity and the response of wages to productivity. In the simple framework analyzed here they cannot both be large.

2.7 Towards an Empirically Observable Wage Elasticity:

While the magnitude of $\frac{\mathrm{d}\log\theta}{\mathrm{d}\log y}$ has been documented in Shimer (2005) no evidence on $\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}}$ is readily available. Even though both components of $\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}}$ are unobservable the goal of this paper is to provide empirical bounds which may help in discriminating between competing approaches to solving the unemployment volatility puzzle. To this end a simple decomposition of the elasticity comes in very handy:

$$\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}} = \frac{\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log w}}{\frac{\mathrm{d}\log\bar{y}}{\mathrm{d}\log y}}\frac{\mathrm{d}\log w}{\mathrm{d}\log y}. \tag{14}$$

Equation 14 describes the relationship between the unobservable $\frac{\mathrm{d}\log\bar{y}}{\mathrm{d}\log\bar{w}}$ and the readily available elasticity of current period wages to current productivity, $\frac{\mathrm{d}\log w}{\mathrm{d}\log y}$ by decomposing it into a ratio of persistence terms for wages and productivity and the current period elasticity of wages to productivity. Furthermore, for any random variable x following an AR(1) process $\frac{\mathrm{d}\log\bar{x}}{\mathrm{d}\log x} = 0$ for a 0 autoregressive coefficient and $\frac{\mathrm{d}\log\bar{x}}{\mathrm{d}\log x} = 1$ for a unit autoregressive coefficient.

While we have no general analytical results for the persistence ratio, simulations reported in table 2 over a wide range of parameters suggest that it is indeed very close to unity for a model with instantaneously rebargained wages and hence the elasticity of the current period wage of newly hired workers with respect to current period productivity, $\frac{\mathrm{d}\log w}{\mathrm{d}\log y}$, constitutes a good proxy for the elasticity of the permanent wage with respect to permanent productivity for the case of instantaneously rebargained wages. On the other hand, with perfect wage rigidity on the job the permanent wage is just proportional to the wage at the time of hiring and hence $\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log w}$ equals unity. Given that $\frac{\mathrm{d}\log\bar{y}}{\mathrm{d}\log y}$ is zero for an *i.i.d* process and unity for a unit root process[8], the elasticity of the current period wage of newly hired workers with respect to current period productivity, $\frac{\mathrm{d}\log w}{\mathrm{d}\log y}$, can be seen as a lower bound for $\frac{\mathrm{d}\log \bar{w}}{\mathrm{d}\log \bar{y}}$ in the case of wage rigidity on the job.

3 Data

The prevailing opinion in the macro literature is that no data are available to test the hypothesis that the wage of new hires might be much more flexible than the aggregate wage (Hall 2005, Bewley 1999). Some anecdotal evidence seems to point against it.[9] To our knowledge, this paper is the first attempt to construct data on the aggregate wage for newly hired workers based on a large dataset that is representative for the whole US labor market. We construct these data at a quarterly frequency for the period 1979-2006 from the Current Population Survey (CPS).

We use data on earnings and hours worked from the CPS outgoing rotation groups, a survey that has been administered every month since 1979 so that our sample period is 1979 to 2006.[10] Wages are hourly earnings (weekly earnings divided by usual weekly hours for weekly workers) and are corrected for top-coding and outliers. We match workers in our survey to the same individuals in three preceding basic monthly datafiles. This allows us to identify newly hired workers as those workers that were not employed[11] for at least one of the three months before we observe their wage. In addition,

[8]Figure 2 illustrates the elasticity $\frac{\mathrm{d}\log \bar{y}}{\mathrm{d}\log y}$ when the autoregressive parameter varies across the unit interval. We note that even for values very close to unity the elasticity is still substantially smaller than one.

[9]According to Bewley, not only "there is little statistical data on the pay of new hires" (1999, p.150), but in addition, "the data that do exist show little downward flexibility.

[10]The BLS started asking questions about earnings in the outgoing rotation group (ORG) surveys in 1979. The March supplement goes back much further (till 1963), but does not allow to construct wage series at higher frequencies than annual. The same is true for the May supplement, the predecessor of the earnings questions in the ORG survey.

[11]Abowd and Zellner (1985) show substantial misclassifications in employment status in the CPS and provide correction factors for labor market flows. Misreporting of employment status also affects our results. A worker who, at some point during the survey period, incorrectly reports not to be employed will then be classified as new hire by our procedure. Hence such misreporting implies that some workers who are actually in ongoing relationships will appear in our series of new hires. Given that we are going to illustrate that the wage of new hires reacts stronger to productivity fluctuations, such misreporting will bias our elasticity estimate downwards. Our procedure is not affected by unemployed erroneously misreporting to be employed because we observe no wage information for them and can therefore detect the misreporting.

we have information on worker characteristics (gender, age, education), industry and occupation. In an average quarter, we have wage data for about 35,000 workers, out of which about 27,000 can be classified to be in ongoing job relationships and 1500 are new hires. The details on the data and the procedure to identify job stayers and new hires are in appendix B.

3.1 Replication of the aggregate wage

Before we proceed to estimation and results, we document that the wage series for all workers that we construct from the CPS roughly corresponds to published series for the aggregate wage. Figure 3 plots our measure for the aggregate wage, constructed from the CPS, and the most commonly used measure for the aggregate wage: hourly compensation in the private non-farm business sector. Both series are nominal and have been seasonally adjusted. Abraham et al. (1999) point out that it is hard to reconcile wage series from different datasets. As documented in that paper, wages from the CPS outgoing rotation groups increase less over the sample period than other measures for the aggregate wage. However, because we (*i*) only include workers in the private, non-farm sector, (*ii*) weigh the average wage by hours worked in addition to the ORG sampling weights, and (*iii*) exclude supervisory workers, as suggested by Abraham et al., the deviation in trend between our series and the aggregate wage is not large and the correlation between both series is almost one.

For the purposes of this paper, it is more important to replicate the cyclical properties of the aggregate wage than the trend. Figures 4, 5, 6 and 7 plot the same two wage series, detrended by various filters roughly in ascending order of focus on high-frequency fluctuations. Figure 4 uses a Hodrick-Prescott (HP) filter with a relative large smoothing parameter of 10^5 (as in Shimer 2004, 2005). It is clear from the graph that we match the low frequency fluctuations well and the correlation between the two series is still very high.[12] However, with this high smoothing parameter, no cyclical pattern is discernable in the wage. In figure 5, we again detrend using the HP filter, but now with a smoothing parameter of 1600 as is standard in the RBC literature (see e.g. King and Rebelo, 1999). With the exception of the 1991-1994 period, our series looks quite similar to the aggregate wage.

The more low frequency fluctuations we remove from the data, the lower becomes the correlation between our wage series and the aggregate wage

[12] Correlation coefficients have been corrected for bias due to sampling error, see section 3.2 and appendix C for details. For the wage of all workers, which we are considering here, this correction is small.

(from 1 without detrending, to 0.86 with a smoothing parameter $\lambda = 10^5$, to 0.56 with $\lambda = 1600$. The reason is that our series, which is calculated as a median (or mean) of a survey sample, is subject to sampling error. By construction, this sampling error is independently distributed (because there is no overlap between our quarterly micro-samples) and therefore contaminates the higher frequencies only. This also explains why our series looks more volatile at high frequencies than the aggregate wage. Figure 6 addresses this issue by using a bandpass filter that blocks both low and high frequencies. We focus on fluctuations with a period of between 6 and 32 quarters, as advocated by Stock and Watson (1999). As is clear from the graph, we match these business cycle frequency fluctuations rather well (again, with the exception of the period 1991-1994).

Figure 7 finally, plots the wage series in first differences. This exacerbates the measurement error, but nevertheless there is strong comovement left between the series, which have a correlation of 0.42 and a regression coefficient from regression the CPS wage on the aggregate wage of 0.77. We conclude that our series are noisier than published series for the aggregate wage, but contain sufficient signal to make the exercise of the paper sensible.

3.2 Business cycle statistics

Our wage series from the CPS looks somewhat similar to the aggregate wage. But does it also display the same properties in terms of volatility, persistence and comovement with other macroeconomic variables? To answer this question, we evaluate the performance of our wage series to match a set of business cycle statistics for the aggregate wage. These statistics are reported in tables 3, 4, 5 and 6 for HP filtered data with a smoothing parameter of 10^5, HP filtered data with a smoothing parameter of 1600, bandpass filtered data and log first differences, respectively. In all these tables, we use real wages, calculated by deflating the nominal series by the implicit deflator for the aggregate wage.[13]

First, consider the set of business cycle statistics for the aggregate wage reported by Shimer (2004). Shimer focuses on the standard deviation (coefficient of variation) and the autocorrelation of the wage, and its correlation with labor productivity, the unemployment rate, vacancies (help-wanted advertising index from the Conference Board) and labor market tightness or the vacancy-unemployment ratio. These statistics are replicated in the top

[13]We also deflated our wage series with the output deflator. For the business cycle statistics, nothing much changes. However, the correlation with the aggregate wage drops substantially if we do not use the same deflator for both series.

panel of table 3, for different sample periods. The first thing to notice is that these moments have changed over time and there are substantial differences in the statistics between Shimer's sample period, 1951-2000 and ours, 1979-2006. It seems likely that these changes are related to the great moderation around 1984, as documented in Gambetti and Galí (2006).[14] The last row of the top panel reports the statistics for the post great moderation period 1984-2006. Comparing these with the statistics for the whole sample, it is clear that the aggregate wage has become substantially more volatile, particularly compared to output and more highly correlated with labor productivity, the source of business cycle fluctuations in most search models.

Next, we calculate the same statistics for the aggregate wage series that we constructed from the CPS. The sampling error in our wage series biases the moments we calculate from these data. This is clearly the case for the variance of the wage, which equals the variance of the true wage series plus the variance of the sampling error. But also the correlation coefficients are biased since they have the standard deviation of the wage in the denominator. However, it is possible to correct for this bias, because we know the standard error of the estimate for the mean (or median) wage that we calculate from the micro-data. All moments in tables 3, 4 and 6 have been corrected for sampling error. In table 5, no correction is necessary because the bandpass filter removes high frequency fluctuations, including the sampling error. Details on the correction are in appendix C.

We use the summary statistics in table 3 to decide how to construct a wage series from the CPS that best matches the cyclical properties of the aggregate wage. To this end, we constructed a large number of wage series, which differ by the workers that are included in the underlying micro-data sample, the measure of centrality (mean or median) and the sampling weights, and compare them in terms of their correlation with the aggregate wage and a set of business cycle statistics. For each series, we calculate the summary statistics both for our full sample period, 1979-2006, and for the post great moderation period, 1984-2006.

The first two rows in the bottom panel of table 3 report summary statistics for the hours-weighted median log real wage for all wage and salary workers. This series has a correlation with the log real aggregate wage

[14] Some of the differences may also be due to sampling error or the filtering procedure. In row 4, we evaluate how much of the effect of the sample period is due to the HP filter. Whether we filter the data on the full sample and then limit the sample to 1979-2006 (as in row 3) or filter the data directly on the 1979-2006 period (as in row 4), does not make much difference for the results.

of 0.47. In terms of business cycle statistics, the standard deviation and persistence are well in line with the aggregate wage. The correlation with unemployment, vacancies and labor market tightness is also similar (basically zero), but the correlation with labor productivity much too low. Rows 3 and 4 consider the same wage series, but calculated for a restricted sample of workers in the private, non-farm business sector only. This brings the CPS wage closer to the aggregate wage, with the correlation increasing to 0.65. Also, the correlation with labor productivity increases, whereas all other statistics look similar. Rows 5 and 6 present statistics for our preferred series, the hours-weighted median log real wage for non-supervisory workers in the private, non-farm business sector. The correlation of this series with the aggregate wages is 0.71, the standard deviation matches almost perfectly that of the aggregate wage and the correlation with labor productivity increases even further, although it is still much lower than for the aggregate wage.

Rows 7 through 12 consider various alternatives to the construction of our preferred series: not weighting the median wage by hours worked, using the mean instead of the median wage or both. All of these alternatives, while somewhat similar to the preferred series, perform less well in replicating the aggregate wage and its cyclical properties.

Table 4 focuses on another set of business cycle statistics (and a different smoothing parameter for the HP filter) that are more commonly used in the RBC literature. The conclusions from comparing the various wage series to the aggregate wage using these statistics are very similar. The correlation with the aggregate wage is highest for our preferred series (0.45). That series matches well the relative standard deviation of the wage with respect to output. It displays only slightly less persistence than the aggregate wage and replicates reasonably well the correlation of the wage with output and hours worked, which is close to zero. Filtering the data with a bandpass filter or by taking log first differences, as in tables 5 and 6, confirms this general picture. The volatility and persistence of the preferred series are very similar to those of the aggregate wage. Like the aggregate wage, the median wage constructed from the CPS is not very correlated with output, labor productivity and other labor market variables.

Finally, as pointed out above, we loose about 20% of the observations in our sample because we cannot classify them as either job stayers or new hires. How does this affect the cyclical properties of the wage? The first two rows of the third panel in tables 3, 4, 5 and 6 present summary statistics for the wage of those workers that can be classified in either category. Across filters, the statistics look very similar to those for the wage of all workers.

4 Results

The main exercise of this paper is to compare the cyclical properties of the wage of newly hired workers to those of the aggregate wage and to the predictions of business cycle models. In section 4.1 we introduce our wage series for newly hired workers and in section 4.2 we evaluate its properties using a standard set of business cycle statistics and find that the wage of new hires is more volatile than the aggregate wage. In sections 4.3 and 4.5, we focus on a particularly relevant business cycle statistic, the elasticity of the wage with respect to productivity shocks. We find that the wage of new hires responds one-to-one to changes in productivity, as the standard (flexible wage) search model would predict. Section 4.4 explores to what extent our results might be driven by various types of composition biases and aims to relate our results to the existing labor literature using individual level panel data.

4.1 The wage of newly hired workers

In figure 8 and 9 we plot the raw data for the wage of workers in ongoing job relationships and the wage of newly hired workers. Each figure also plots the wage of all workers for comparison. The trend in the three wage series is very similar, but workers in ongoing jobs on average have a much higher wage than newly hired workers. This is not surprising, since newly hired workers include disproportionately many workers at the beginning of their career and we know from the labor literature that there are substantial returns to experience. While we could easily correct for this difference in average experience, we do not do so because we are not interested in the trends in this paper. In section 4.4.1 we explore the robustness of our results to this choice.

The graphs also show two-standard-error bands around the wage series for job stayers and new hires. Since our series are simply means (or medians) of the underlying micro-data on wages, these standard errors are straightforward to calculate, see appendix B. The wage for job stayers is fairly tightly estimated, but the standard errors for the wage of new hires are much larger, reflecting the fact that in each quarter, only about 5% of workers are in new matches so that the sample size for newly hired workers is much smaller. This makes the wage for new hires look more volatile, which is why the bias correction of the business cycle moments is particularly important for this group, see appendix C.

To have a first look at the cyclical properties of these wages, figures 10 and 11 present the same wages series, detrended using the bandpass filter that passes fluctuations with periodicity between 6 and 32 quarters. We focus on the bandpass filtered data because they are less affected by the sampling error in the wage series. As is clear from figure 10, the business cycle fluctuations in the wage of workers in ongoing jobs looks very similar to the fluctuations in the wage for all workers. Neither series is very volatile and neither shows a clear comovement with the NBER business cycle dates. The wage of newly hired workers in figure 11 however, is not only much more volatile than the aggregate wage, but shows a pronounced countercyclical pattern, particularly in the first two recessions. This finding is consistent with high inflation expectations at the time of wage negotiations and low inflation realizations, as in fact happened in this transition period between monetary policy regimes.

4.2 Business cycle statistics

Consider again the set of business cycle statistics for labor market variables as in Shimer (2004, 2005) in table 3 and the RBC statistics in table 4. The third panel of the tables presents these statistics for the wage of all (validly matched) workers, workers in ongoing job relationships and newly hired workers. The wage for job stayers looks consistently very similar to the wage of all workers, because of the fact that in any given quarter, the vast majority of workers (about 95%) are in ongoing job relationships.

As is clear from table 3, the standard deviation of the wage of new hires is about twice as high as for the wage of all workers and an F-test overwhelmingly rejects the null that the two variances are equal. The wage of new hires is also somewhat less persistent, although the difference is small. Table 4 gives a very similar picture: the relative standard deviation is substantially higher and persistence substantially lower for the wage of new hires. Tables 5 and 6 show that these results are not specific to the HP filter. Also, our conclusions are the same, and often even starker, if we use the mean instead of the median wage for each group, as reported in rows 7 through 12 of all four tables. This is our first piece of evidence that the wage for newly hired workers seems much less rigid than the aggregate wage.

Compared to the predictions of a standard search model with flexible wage, see table 2, we find that the standard deviation of the wage of new hires is about two times higher rather than lower than the model predicts, see table 3. The same is true for the relative standard deviation of wages with respect to output, see table 4, compared to a standard real business cycle (RBC) model, which predicts a relative standard deviation of wages of about 0.54 (King and Rebelo 1999). Compared to either model, the wage of newly hired workers is also slightly less rather than more persistent than the model predicts, with an autocorrelation of 0.79 and 0.46 for HP filtered data with smoothing parameters 10^5 or 1600 respectively, compared to 0.85 for the search model (Shimer 2004) and 0.76 for the RBC model (King and Rebelo 1999).

We also find some evidence that the volatility of the wage of new hires has not changed much around the great moderation, so that the relative volatility increases because output becomes less volatile. This is consistent with the findings of Galí and Gambetti (2007), although our result should be interpreted with caution because we only have five years of data prior to 1984.

4.3 Elasticity of the wage with respect to productivity

We now focus on a particularly relevant business cycle statistic: the coefficient of a regression of the log real wage on log real labor productivity. This statistic is obviously very similar to the correlation of wages with productivity, but has a more natural interpretation as the elasticity of wages with respect to productivity. In a model that is driven by productivity shocks only, like the standard stochastic search model we described in section 2, this elasticity provides an intuitive measure of wage rigidity. If wages are perfectly flexible, they respond one-for-one to changes in productivity, whereas an elasticity of zero corresponds to perfectly rigid wages.

As pointed out by Hagedorn and Manovskii (2006), the elasticity of wages with respect to productivity is a better summary statistic for calibrating the search model than the correlation or elasticity of wages with other variables, like the unemployment rate, vacancies or labor market tightness. There are at least three reasons for this. First, in the model, other labor market variables are endogenous, but productivity is exogenous. Therefore, a regression of log wages on log productivity will deliver an unbiased estimate of the elasticity. Second, the coefficient of a regression of wages on unemployment or vacancies is inversely proportional to the variance of these variables. If we are evaluating the performance of the model to match these variances, then we do not want to target them in the calibration. Third, it is likely that composition bias affects the cyclicality of wages if we use, for example, the unemployment rate as a cyclical indicator. Solon, Barsky and Parker (1994) show that, in a recession, firms hire on average more skilled workers than in a boom. Because more skilled workers are more productive, this drives up wages in a recession. It is unlikely however, that it affects the elasticity of wages with respect to labor productivity, because workers' skill level affects productivity and wages proportionally. This composition bias may explain why we find wages to be countercyclical with respect to unemployment, vacancies and labor market tightness in the previous section. We explore this issue in more detail in section 4.4.1.

In the context of this paper, there are additional advantages of using the elasticity rather than the correlation of wages with productivity. Our wage series are subject to (intertemporally uncorrelated) measurement error. This biases the volatility of wages and therefore their correlation with other variables, see appendix C. In a regression however, measurement error in the dependent variable does not bias the coefficient. Moreover, the coefficient has a clear causal interpretation as an elasticity, it is straightforward to calculate standard errors and we can easily control for other factors that affect wages if necessary.

In order to avoid a spuriously high elasticity if wages and productivity are integrated, we estimate our regression in first differences.

$$\Delta \log w_{jt} = \alpha_j + \xi_j \Delta \log y_t + \varepsilon_{jt} \tag{15}$$

where w_{jt} denotes the real wage of subgroup $j \in \{\text{all workers, job stayers, new hires}\}$ and y_t is labor productivity. Estimating in first differences has the additional advantage that we do not have to detrend the data using a filter, which changes the information structure of the data and therefore makes it harder to give a causal interpretation to the coefficient.

Notice that w_{jt} in equation (15) is itself an estimate from the underlying individual level wage data. Previous studies on the cyclicality of wages, starting with Bils (1985), have collapsed the two steps of the estimation procedure into one, and directly estimated the following specification from the micro data.

$$\Delta \log w_{ijt} = \alpha_j + \xi_j \Delta \log y_t + \varepsilon_{ijt} \tag{16}$$

where w_{ijt} denotes the wage of individual i, belonging to subgroup j, at time t. However, because the wage last quarter is unobserved for newly hired workers (since they were not employed), this approach is not feasible for our purpose. Therefore, we implement our procedure as a two-step estimator and estimate (15) from aggregate wage series. In section 4.4 we explore the differences between the two approaches.

Estimation results for the elasticity of various wage series with respect to productivity are reported in the first row of table 7. All regressions include quarter dummies to control for seasonality but are otherwise as in equation

(15). For each regression, we report the estimate for ξ_j, the standard error and the number of quarterly observations.

We start with reporting the elasticity for the aggregate wage (compensation per hour for the private, non-farm business sector from the BLS productivity and cost program). The elasticity is similar for the full 1947:II-2006:I sample and for the 1951:I-2001:IV subsample and is about 0.27 with a standard error of 0.05. This is lower than the elasticity of 0.45 reported by Hagedorn and Manovskii (2006), who run the regression in levels on HP filtered data (smoothing parameter 1600). The number changes very little when we restrict the sample to the period for which our CPS wage series are available, 1979:II-2006:I.

Using the mean wage of all non-supervisory workers in the private, nonfarm sector from the CPS, the elasticity is a bit lower, but the difference is not significant. For newly hired workers however, the elasticity increases substantially, although the standard error also increases. For the post great moderation period, 1984:I-2006:I, the picture is even starker. All wage series become more procyclical over this period. The wage of new hires, now responds almost one-for-one to changes in labor productivity, with an elasticity of 0.94. All these results are similar if we use median instead of mean wages or if we weight the regression by the inverse of the variance of the first step estimates.

Across specifications, the elasticity of the wage of new hires with respect to productivity is much higher than the elasticity of the wage of all workers. For the post 1984 period, the point estimates are close to one, never significantly different from one and often significantly different from zero. Thus, we do not find any evidence for wage rigidity in the wage of new hires and therefore in permanent wages, at least for the period after the great moderation.

4.4 Composition bias

In section 2 we argued that the wage that matters for employment fluctuations is the wage of new hires. In the model, newly formed matches are, by assumption, identical to other matches in the economy. Therefore, the average wage received by workers that are hired in any given quarter is representative for the wage that any worker would receive in a job that started in that quarter.

In the data, however, workers and jobs are heterogeneous and wages of newly hired workers may not be a representative subsample of the whole labor force. The observation that new hires have lower than average wages, see figure 9, is consistent with a larger fraction of poorly educated (Figure 13) and less experienced (Figure 14) among the new hires. If, moreover, the composition of newly hired workers or newly formed jobs varies over the business cycle, then this heterogeneity will bias our estimate of the response of wages to productivity.

4.4.1 Heterogeneous workers

Taking into account individual heterogeneity, we can write the level wage equation as

$$\log w_{ijt} = \alpha_j t + x_{ij}'\beta + \xi_j \log y_t + u_{ijt} \tag{17}$$

where $\Delta u_{ijt} = \varepsilon_{ijt}$ and x_{ij} is a vector of individual-specific but time-invariant characteristics.

Following Bils (1985), the standard approach in the micro-literature has been to first difference this equation, so that the individual heterogeneity terms drop out. However, the need to first difference the wage limits the analysis to workers that were employed both in the current and in the previous quarter and thus does not allow to consider the wage of newly hired workers. Therefore, we take a different approach and proxy x_{ij} by a vector of observables: gender, race, marital status, education and experience.

Aggregating by quarter and first differencing, we get

$$\Delta \log w_{jt} = \alpha_j + \Delta x_{jt}'\beta + \xi_j \Delta \log y_t + \varepsilon_{ijt} \tag{18}$$

Notice that although we may assume worker characteristics to be time-invariant for an individual, the average characteristics of the labor force x_{jt} vary with time because the composition of the labor force changes. To implement this regression as a 2-step procedure, we first regress individual wages on individual characteristics (in levels) and calculate a composition bias corrected wage series as $\log \tilde{w}_{jt} = \log w_{jt} - (x_{jt} - \bar{x}_j)' \beta$. In the second step, we then regress corrected wages on productivity in first differences to get ξ_j.

The results of these regressions are presented in rows 2 and 3 of table 7. In row 2, we control only for education level, in row 3 in addition for demographic characteristics like gender, race, ethnicity and marital status. The elasticity of the various wage series with respect to productivity remains virtually unaltered when we control for this heterogeneity.

4.4.2 Comparison with the literature

The main methodological difference between our study and previous work, which allows us to explore the cyclicality in the wage of newly hired workers, is that we use the first difference of the average wage, rather than the average first difference of the wage, as the dependent variable. This raises the question whether our approach to control for composition bias using observable worker characteristics is sufficient to control for all worker heterogeneity. To explore this issue, we re-estimated the results in Devereux (2001), the most recent paper that is comparable to ours.[15]

The first two columns of table 8 replicate Devereux's (2001) estimates for workers in ongoing relationships and the wage of all workers, The elasticity of the aggregate wage with respect to unemployment in the PSID is about -1, well in line with our estimates from the CPS. Wages of job stayers are somewhat less cyclical.

We now re-estimate these numbers using an estimation approach that is gradually more similar to ours. First, we leave out the controls for labor market experience and job tenure. This changes the estimates very little. Next, we directly estimate the elasticities from the micro-data, clustering the standard errors, rather than employing a 2-step procedure. Again, this leaves the estimates and their standard errors virtually unchanged. Then, we use the 2-step procedure that we use for the CPS, first aggregating wages in levels and then estimating the elasticity in first differences. This procedure gives rather different estimates. However, when we include controls for education and demographic characteristics, the estimates are once again very close to those in Devereux (2001). Our procedure is less efficient than the one used by Devereux so that our standard errors are larger We conclude that, although less efficient, our procedure to control for individual heterogeneity using observable worker characteristics works well.

Finally, we use the PSID data to estimate the elasticity of the wage of job changers with respect to productivity. It responds one-to-one to changes in productivity, which leads us to conclude that the estimates for job changers

[15] We are grateful to Paul Devereux for making his data available to us. To our knowledge, Devereux (2001) is the most recent paper with estimates comparable to ours from the PSID. Devereux and Hart (2006) use UK data. Barlevy (2001) regresses wages on state-level unemployment rates and includes interactions of the unemployment rate with unemployment insurance. Other more recent papers (Grant 2003, Shin and Solon 2006) use the NLSY. While the NLSY may be well suited to explore some interesting questions closely related to the topic of this paper (in particular, the cyclicality of the wage of job changers because of the much larger number of observations for this particular group of workers), it is not a representative sample of the US labor force.

and workers that are newly hired out of non-employment are comparable. The standard error, however, at 0.8 is very large, even with the more efficient Devereux procedure to control for heterogeneity, and much larger than the standard error for the elasticity of the wage of new hires based on our CPS data.

4.4.3 Heterogeneous jobs

It is possible that not only the workers that are hired are different between recessions and booms, but the jobs that are created are different as well. In particular, there is some evidence that matches created in a boom pay higher wages and last longer than matches created in a recession (Beaudry and DiNardo 1991, Davis, Haltiwanger and Schuh 1996). If this is the case, then the wage of newly hired workers seems more procyclical than it is, because workers that are hired in a recession receive higher wages not just because aggregate productivity is higher, but also because they are in a permanently better match. In addition, it is possible that new hires are disproportionately likely to be in a few high-turnover, flexible-wage industries like food services.

To control for this composition bias originating from heterogeneity in jobs, we construct a set of industry weights to make the sample of new hires representative for the whole labor force. These weights are based on a consistent industry classification over the whole sample period that roughly corresponds to a 2-digit NAICS classification. These estimates are presented in row 6 of panels A and B in table 7. Keeping industry composition constant, the elasticity of the wage of new hires with respect to productivity drops by about 20%, bridging about one fourth of the gap between the elasticity of the wage of new hires and the wage of all workers. For men only (c.f. Table 9) composition estimates are almost unaffected by controlling for industry composition.

While heterogeneity in jobs is not the whole story for why wage of new hires are so much more flexible than wages of all workers, it does explain part of the difference. This finding lends some support to Reiter's (2006) argument that part of the unemployment volatility puzzle can be explained by technological change that is embodied in a match.

4.5 Response of wages to technology shocks

Our estimates for the elasticity of wages to productivity are unbiased under the search model, because labor productivity is exogenous. In this section we explore to what extent the exogeneity assumption matters in a more general model with capital or in the presence of other shocks to the economy.

Suppose production requires capital as well as labor and is of the Cobb-Douglas form with diminishing returns to total hours, $Y_t = A_t K_t^{\alpha} L^{1-\alpha}$, where A_t is total factor productivity, K_t is capital and L_t is total hours. Log total factor productivity equals $\log A_t = \log Y_t - \alpha \log K_t - (1-\alpha)\log L_t$, whereas log labor productivity is given by $\log y_t = \log Y_t - \log L_t = \log A_t + \alpha \log K_t - \alpha \log L_t$. This illustrates the problem of endogenous fluctuations in total hours. If what we are interested in is total factor productivity, then log labor productivity is endogenous because of the $\alpha \log L_t$ term. Ignoring fluctuations in the capital stock, which are small compared to fluctuations in labor at high frequencies, we can construct a quarterly productivity series corrected for endogenous fluctuations in total hours as $\log \tilde{y}_t = \log y_t + \alpha \log L_t$. When we use this corrected productivity series, as in the second panel of table 7, the elasticity of the aggregate wage, the wage of all workers, all validly matched workers, job stayers and newly hired workers with respect to productivity changes very little, suggesting that the bias because of endogenous fluctuations in employment is small.

If there are other shocks than just productivity shocks that generate fluctuations in wages, then the unconditional moments may give the wrong picture. Therefore, we also estimate the conditional response of wages to technology shocks using a structural vector autoregression (VAR) model. We identify permanent technology shocks using a VAR with labor productivity and total hours worked and a long run restriction as in Galí (1999). We estimate this VAR with 2 lags in first differences and take the residuals as our measure of changes in productivity. The results for elasticity of wages with respect to these identified technology shocks are presented in the third panel of table 7. Overall, the response of wage to these identified technology shocks is somewhat lower than to labor productivity, with a baseline elasticity between 0.6 and 0.7 for the wage of new hires and 0 to 0.2 for the wage of all workers.

Finally, figure 18 presents impulse responses of the same VAR, extended with the wage as a third variable. The estimated impulse responses to technology shocks closely replicate Galí's findings: technology shocks increase labor productivity in the long run (by construction) and reduce hours worked. Hours shocks (or 'demand shocks') temporarily increase productivity and increase hours worked. The third shock, or wage shock, has a negligible effect on both productivity and hours, indicating that the two-variable VAR was well-specified. This shock explains an important part of the variability in wages. Partly, this is due to measurement error in our wage series: the spike in the impact response of wages to the wage shock indicates serially uncorrelated shocks to the wage. The response of the wage to technology shocks is imprecisely estimated, but nevertheless informative. Figure 19 plots this response both for the wage of all workers and for the wage of new hires and displays the familiar picture that wages of newly hired workers are much more responsive to productivity shocks than the aggregate wage.

5 Conclusions/Discussion

In this paper we construct an aggregate time series for the wage of workers newly hired out of non-employment. We find that these wages of newly hired workers react strongly to productivity fluctuations with an elasticity of one whereas wages of workers in ongoing job relationships react very little to productivity fluctuations.

For newly hired workers we illustrate that this elasticity is a lower bound for the elasticity of permanent wages with respect to permanent productivity, which is the key wage elasticity in the search and matching model in determining labor market tightness fluctuations.

Therefore our empirical results are evidence against several common assumptions in the literature that imply rigidity in the wage of newly hired workers as in Hall (2005), Gertler and Trigari (2006) or Blanchard and Galí (2006). We conclude that wage rigidity cannot be the solution to the Shimer (2005) puzzle and propose to focus more on job creation rather than alternative wage determination mechanisms as for example Reiter (2006).

A Derivation of the wage equation

to be completed ...

B Description of the data

We use wage data for individual workers in the CPS outgoing rotation groups from 1979 to 2006. We match these workers to the three preceding basic monthly datafiles in order to construct four months (one quarter) of employment history, which we use to identify newly hired workers. The outgoing rotation group data are available from http://www.ceprdata.org/cps/org_index.php and the basic monthly datafiles from http://www.nber.org/data/cps_basic.html. Stata do-files to create our matched datasets with uniform variable definitions over time are available from the authors on request and will be posted in due time at http://www.econ.upf.edu/~vanrens/wage.

B.1 Wages from the CPS outgoing rotation groups

We consider only wage and salary workers that are not self-employed and report non-zero earnings and hours worked. Both genders and all ages are included in our baseline sample. Our wage measure is hourly earnings (on the main job) for hourly workers and weekly earnings divided by usual weekly hours for weekly workers. For weekly workers who report that their hours vary (from 1994 onwards), we use hours worked last week. Top-coded weekly earnings are imputed assuming a log-normal cross-sectional distribution for earnings, following Schmitt (2003), who finds that this method better replicates aggregate wage series than multiplying by a fixed factor or imputing using different distributions. Notice that the imputation of top-coded earnings affects the mean, but not the median wage.

Outliers introduce extra sampling variation. Therefore, we mostly use median wages throughout the paper. For mean wages, we follow the literature and apply mild trimming to the cross-sectional distribution of hours worked (lowest and highest 0.5 percentile) and hourly wages (0.3 percentiles). These values roughly correspond to USD 1 per hour and USD 100 per hour at constant 2002 dollars, the values recommended by Schmitt (2003). We prefer trimming by quantiles rather than absolute levels because (*i*) it is symmetric and therefore does not affect the median, (*ii*) it is not affected by real wage growth and (*iii*) it is not affected by increased wage dispersion over the sample period.

We do not correct wages for overtime, tips and commissions, because (*i*) the relevant wage for our purposes is the wage paid by employers, which includes these secondary benefits, (*ii*) the data necessary to do this are not available over the whole sample period, and (*iii*) this correction has very little effect on the average wage (Schmitt 2003). We also do not exclude allocated earnings because (*i*) doing so might bias our estimate for the average wage and (*ii*) allocation flags are not available for all years and (*iii*) even if they are only about 25% of allocated observations are flagged as such (Hirsch and Schumacher 2004).

Mean and median wages in a given month are weighted by the appropriate sampling weights (the earnings weights for the outgoing rotation groups) and by hours worked, following Abraham et al. (1999) and Schmitt (2003). We explore robustness to the weights and confirm the finding of these papers that hours weighted series better replicate the aggregate wage. Average mean or median wages in a quarter are simple averages of the monthly mean or median wages. Contrary to some of the literature, we consider log mean wages rather than mean log wages. In order to correct the business cycle statistics for the wage for sampling error (see appendix C), we calculate standard errors for mean and median wages. Standard errors for the mean are simply the standard deviation of the wage divided by the square root of the number of observations. Medians are also asymptotically normal, but their variance is downward biased in small samples. Therefore, we bootstrap these standard errors.

We seasonally adjust our wage series by regressing the log wage on quarter dummies. Nominal wages are deflated by the implicit deflator for hourly earnings in the private non-farm business sector (chain-weighted) from the BLS productivity and costs program. Using different deflators affects the results very little, but decreases the correlation of our wage series with the aggregate wage.

We identify private sector workers using reported 'class of worker'. We construct an industry classification that is consistent over the whole sample period (building on the NBER consistent industry classification but extending it for data from 2003 onwards). We use this industry variable to identify farm workers and to exploit cross-industry variation in wages and productivity, see section 4.4.3. We identify supervisory workers using reported occupation. Because of the change in the BLS occupation classification in 2003, there is a slight jump in the fraction of supervisory workers from 2002:IV to 2003:I. It is not possible to distinguish supervisory workers in agriculture or the military, so all workers in these sectors are excluded in the wage series for non-supervisory workers.

Finally, in order to control for composition bias because of heterogeneous workers (see section 4.4.1), we need additional worker characteristics to use in a Mincerian earnings regression. Dummies for females, blacks, hispanics and married workers (with spouse present) are, or can be made, consistent over the sample period. We construct a consistent education variable in five categories as well as an almost consistent measure for years of schooling following Jaeger (1997) and calculate potential experience as age minus years of schooling minus six.

B.2 Identifying newly hired workers

We match the individuals in the outgoing rotation groups to the three preceding basic monthly data files using household ID, household number (for multiple households on one address), person line number (for multiple wage earners in one household), month-in-sample and state. To identify mismatches, we use the s|r|a criterion from Madrian and Lefgren (2000). A worker is flagged as a mismatch if gender or race changes between two subsequent months or if the difference in age is less than 0 or greater than 2 (to allow for some measurement error in the reported age). Madrian and Lefgren show that this criterion performs well in the trade-off between false matches and false mismatches. Within the set of measures that they find to perform well, s|r|a is the strictest. We choose a strict criterion because mismatches are more likely to be classified as newly hired workers (see below) and are therefore likely to affect our results substantially.

We can credible match about 80% of workers in the outgoing rotation group to all three preceding monthly files. Because of changes in the sample design, we cannot match sufficiently many individuals to the preceding four months in the third and fourth quarter of 1985 and in the third and fourth quarter of 1995, so that the wage series for validly matched workers, job stayers and new hires have missing values in those quarters. In our regressions, we weight quarters by the variance of the estimate for the mean or median wage so that quarters with less than average number of observations automatically get less weight.

Including the outgoing rotation group itself, the matched data include four months employment history (employed, unemployed or not-in-the-labor-force), which we obtain from the BLS labor force status recode variable. We use this employment history to identify newly hired workers and workers in ongoing job relationships. New hires are defined as workers that were either unemployed or not in the labor force for any of the preceding three months. Job stayers are identified as workers that were employed for all four months.

Notice that the two groups are not comprehensive for the group of all workers, because workers that cannot be matched to all preceding months can not always be classified.

C Correcting business cycle statistics for sampling error

We estimate wages for all workers, job stayers and new hires from an underlying micro-data survey. Therefore, our wage series are subject to sampling error. Given the way we construct these series, we know three things about the sampling error. First, because there is no overlap between individuals included in the outgoing rotation groups in two subsequent quarters, the sampling error is uncorrelated over time.[16] Second, because the sampling error in each period is the error associated with estimating a mean (or median), it is asymptotically normally distributed. Third, we have an estimate for the standard deviation of the sampling error in each quarter, which is given by the standard error of the mean (or median) wage in that quarter. Notice that taking first difference exacerbates the measurement error, increasing the standard deviation by a factor $\sqrt{2}$. Because of these three properties, and because the estimated standard errors are stable over time, we can treat the sampling error as classical measurement error, which is independent and identically distributed.

Let w_t denote an estimated wage series, $w_t = w_t^* + \varepsilon_t$, where w_t^* is the true wage and ε_t is the sampling error in the wage, which is uncorrelated over time and with w_t^* and has a known variance σ^2. The business cycle statistics we consider are the standard deviation of w_t^*, the autocorrelation of w_t^* and the correlation of w_t^* with x_t, an aggregate variable that is not subject to measurement error. These statistics can be calculated from the estimated wage series w_t and the estimated standard deviation of the sampling error σ as follows.

$$var\left(w_t\right) = var\left(w_t^*\right) + \sigma^2 \Rightarrow sd\left(w_t^*\right) = \sqrt{R} \cdot sd\left(w_t\right)$$

[16] Individuals in the CPS are interviewed four months in a row, the last one of which is an outgoing rotation group, then leave the sample for eight months, after which they are interviewed another four months, the last one of which is again an outgoing rotation group. Therefore, about half of the sample in quarter t (individuals in rotation group 8) is also included in the sample in quarter $t-4$ (when they were in rotation group 4) and the other half is included in the sample in quarter $t+4$. Thus, the sampling error may be correlated with a four quarter lag, but not between subsequent quarters. We ignore this correlation structure and treat the sampling error as uncorrelated over time.

$$cov\left(w_t, w_{t-1}\right) = cov\left(w_t^*, w_{t-1}^*\right) \Rightarrow corr\left(w_t^*, w_{t-1}^*\right) = \frac{corr\left(w_t, w_{t-1}\right)}{R}$$

$$cov\left(w_t, x_t\right) = cov\left(w_t^*, x_t\right) \Rightarrow corr\left(w_t^*, x_t\right) = \frac{corr\left(w_t, x_t\right)}{\sqrt{R}}$$

where $R = \left(var\left(w_t\right) - \sigma^2\right) / var\left(w_t\right) \in (0, 1)$ is the fraction of signal in the variance of w_t. Unless explicitly specified, we use the correction factors $\sqrt{R}$, $1/R$ and $1/\sqrt{R}$ for all reported business cycle statistics. This bias correction is small for the wages of all workers and job stayers, because sample sizes are large and therefore σ^2 is small, but substantial for the wage of new hires. Notice that the bias correction decreases the reported standard deviations towards zero but increases the reported autocovariances and correlation coefficients away from zero. Regression coefficients for the wage on labor productivity are not biased in the presence of classical measurement error in the dependent variable so no correction is necessary.

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Table 1: Simulation Results

Model	$\frac{\mathrm{d}\log\bar{w}}{\mathrm{d}\log\bar{y}}$	$\frac{\mathrm{d}\log w^n}{\mathrm{d}\log y}$	$\frac{\mathrm{d}\log w^s}{\mathrm{d}\log y}$	$\frac{\mathrm{d}\log w^a}{\mathrm{d}\log y}$	$\frac{\mathrm{d}\log\theta}{\mathrm{d}\log y}$	$\frac{\sigma_u}{\sigma_y}$
Shimer, AER calibration	0.985	0.986	0.986	0.986	1.646	0.413
Small Surplus calibration	0.384	0.389	0.389	0.389	46.516	11.706
Countercyclical Bargaining power	0.601	0.228	0.228	0.228	24.028	6.002
Zero Worker Bargaining Power	-0.004	0.000	0.000	0.000	1.502	0.383
On the job wage rigidity	0.985	0.648	0.159	0.163	1.646	0.413

Elasticities are averages of 1000 replicatons of length 89 quarters. The models are simulated at weekly frequency and aggregated to quarterly data before computing statistics. All data has been logged and detrended using HP-filters. Parameters are chosen as in Shimer (2005) except for the small surplus calibration where the flow utility of unemployment is 0.98 of per period productivity and the worker bargaining power is 0.05. For each simulation the vacancy posting cost is chosen to normalize steady state labor market tightness to unity.

Table 2: Elasticities for the flexible wage model

b	β	$\frac{d\log\bar{w}}{d\log\bar{y}}$	$\frac{d\log w}{d\log\bar{y}}$	$\frac{d\log w}{d\log y}$	$\frac{d\log\bar{w}}{d\log w}$	$\frac{d\log\bar{y}}{d\log y}$	$\frac{d\log\theta}{d\log y}$	$\frac{\sigma_\theta}{\sigma_y}$	$\frac{\sigma_u}{\sigma_y}$
0.000	0.010	0.912	1.415	0.919	0.645	0.650	0.912	0.912	0.186
0.000	0.050	0.943	1.454	0.944	0.649	0.649	0.936	0.936	0.191
0.000	0.100	0.960	1.480	0.961	0.649	0.650	0.953	0.953	0.194
0.000	0.300	0.985	1.517	0.985	0.650	0.650	0.977	0.977	0.199
0.000	0.500	0.993	1.529	0.993	0.649	0.650	0.985	0.985	0.201
0.000	0.700	0.997	1.535	0.997	0.650	0.650	0.989	0.989	0.202
0.000	0.900	0.999	1.538	0.999	0.650	0.650	0.991	0.991	0.203
0.000	0.950	1.000	1.539	1.000	0.650	0.650	0.991	0.991	0.203
0.200	0.010	0.345	0.563	0.366	0.613	0.650	1.140	1.140	0.233
0.200	0.050	0.727	1.126	0.732	0.646	0.650	1.171	1.171	0.240
0.200	0.100	0.843	1.300	0.845	0.648	0.650	1.191	1.192	0.243
0.200	0.300	0.951	1.464	0.951	0.649	0.650	1.221	1.221	0.250
0.200	0.500	0.978	1.505	0.978	0.650	0.650	1.231	1.231	0.251
0.200	0.700	0.990	1.524	0.990	0.650	0.650	1.236	1.236	0.252
0.200	0.900	0.997	1.535	0.997	0.650	0.650	1.239	1.239	0.254
0.200	0.950	0.999	1.537	0.999	0.650	0.650	1.239	1.239	0.253
0.400	0.010	0.213	0.351	0.228	0.605	0.650	1.520	1.520	0.311
0.400	0.050	0.592	0.920	0.598	0.643	0.650	1.561	1.561	0.319
0.400	0.100	0.751	1.160	0.754	0.647	0.650	1.588	1.588	0.324
0.400	0.300	0.919	1.415	0.920	0.649	0.650	1.627	1.627	0.333
0.400	0.500	0.963	1.483	0.964	0.650	0.650	1.641	1.642	0.335
0.400	0.700	0.984	1.514	0.984	0.650	0.650	1.647	1.647	0.338
0.400	0.900	0.996	1.532	0.996	0.650	0.650	1.652	1.653	0.338
0.400	0.950	0.998	1.536	0.998	0.650	0.650	1.651	1.651	0.338
0.600	0.010	0.154	0.256	0.166	0.602	0.650	2.277	2.277	0.466
0.600	0.050	0.499	0.777	0.505	0.642	0.650	2.341	2.342	0.479
0.600	0.100	0.677	1.047	0.680	0.646	0.650	2.381	2.381	0.486
0.600	0.300	0.889	1.369	0.890	0.649	0.650	2.443	2.444	0.499
0.600	0.500	0.949	1.461	0.949	0.650	0.650	2.462	2.463	0.503
0.600	0.700	0.977	1.504	0.978	0.650	0.650	2.471	2.472	0.505
0.600	0.900	0.994	1.530	0.994	0.650	0.650	2.478	2.478	0.507
0.600	0.950	0.997	1.535	0.997	0.650	0.650	2.476	2.477	0.506
0.800	0.010	0.120	0.201	0.130	0.600	0.650	4.553	4.555	0.932
0.800	0.050	0.431	0.672	0.437	0.641	0.650	4.684	4.686	0.957
0.800	0.100	0.616	0.954	0.620	0.646	0.650	4.761	4.763	0.975
0.800	0.300	0.861	1.327	0.862	0.649	0.650	4.878	4.880	0.998
0.800	0.500	0.935	1.440	0.936	0.649	0.650	4.921	4.923	1.007
0.800	0.700	0.971	1.494	0.971	0.650	0.650	4.945	4.948	1.011
0.800	0.900	0.992	1.527	0.992	0.650	0.650	4.949	4.951	1.013
0.800	0.950	0.996	1.533	0.996	0.650	0.650	4.956	4.959	1.013
0.980	0.010	0.101	0.168	0.109	0.599	0.650	45.499	45.531	9.300
0.980	0.050	0.384	0.600	0.390	0.640	0.650	46.749	46.782	9.542
0.980	0.100	0.570	0.884	0.574	0.645	0.649	47.518	47.554	9.721
0.980	0.300	0.837	1.291	0.839	0.648	0.650	48.772	48.811	9.979
0.980	0.500	0.923	1.422	0.924	0.649	0.649	49.103	49.144	10.046
0.980	0.700	0.966	1.487	0.966	0.649	0.650	49.352	49.392	10.107
0.980	0.900	0.991	1.525	0.991	0.650	0.650	49.486	49.528	10.129
0.980	0.950	0.996	1.533	0.996	0.650	0.650	49.472	49.512	10.141

Elasticities are averages of 1000 simulations of length 89 quarters. All data are in log first differences.

Table 3: Business cycle statistics (logs, HP filtered, $\lambda = 100,000$).

Table 3. Business cycle statistics (HP filtered, smoothing parameter 100,000)

	sample period		correlation aggregate wage	standard deviation	relative standard deviation	auto-correlation	correlation: output	hours	labor productiv.	unempl	vacancies	labor market tightn.
Aggregate wage												
1	1947	2006	1.00	0.014	0.44	0.90	0.18	-0.01	0.36	-0.03	-0.01	0.02
2	1951	2001	1.00	0.014	0.43	0.91	0.20	0.05	0.31	-0.08	0.05	0.08
3	1979	2006	1.00	0.016	0.59	0.93	0.15	-0.16	0.58	0.04	-0.18	-0.12
4	1979	2006	1.00	0.016	0.59	0.93	0.14	-0.18	0.62	0.04	-0.21	-0.14
5	1984	2006	1.00	0.018	0.84	0.93	0.14	-0.25	0.69	0.12	-0.29	-0.22
CPS wage for all workers												
1 Median, hours weighted, all sectors	1979	2006	0.47	0.018	0.61	0.89	0.31	0.25	0.10	-0.26	0.05	0.15
2	1984	2006	0.47	0.018	0.81	0.91	0.32	0.22	0.06	-0.21	-0.03	0.07
3 Median, hours weighted, private nfm	1979	2006	0.65	0.018	0.61	0.86	0.15	0.03	0.23	-0.04	-0.15	-0.07
4	1984	2006	0.65	0.019	0.83	0.88	0.19	0.01	0.26	0.01	-0.20	-0.12
5 Median, hours weighted, private nfm, non-superv.	1979	2006	0.71	0.017	0.55	0.87	0.33	0.12	0.39	-0.21	0.03	0.11
6	1984	2006	0.71	0.017	0.74	0.88	0.30	0.02	0.41	-0.09	-0.08	-0.01
7 Median, private nfm, non-superv.	1979	2006	0.57	0.019	0.63	0.84	0.39	0.19	0.36	-0.28	0.08	0.17
8	1984	2006	0.57	0.017	0.76	0.82	0.27	0.06	0.30	-0.08	-0.10	-0.02
9 Mean, hours weighted, private nfm, non-superv.	1979	2006	0.57	0.015	0.52	0.88	0.26	0.15	0.20	-0.20	-0.04	0.07
10	1984	2006	0.57	0.016	0.68	0.87	0.25	0.11	0.17	-0.11	-0.11	-0.02
11 Mean, private nfm, non-superv.	1979	2006	0.54	0.016	0.54	0.88	0.26	0.17	0.17	-0.22	-0.02	0.09
12	1984	2006	0.54	0.016	0.69	0.87	0.24	0.12	0.13	-0.12	-0.11	-0.01
CPS wage (hours weighted, private nfm, non-superv.)												
1 All matched workers, median	1979	2006	0.70	0.017	0.55	0.89	0.24	0.01	0.44	-0.09	-0.07	0.00
2	1984	2006	0.70	0.018	0.75	0.91	0.20	-0.08	0.46	0.04	-0.18	-0.12
3 Job stayers, median	1979	2006		0.018	0.57	0.82	0.18	-0.05	0.44	-0.03	-0.14	-0.07
4	1984	2006		0.018	0.76	0.81	0.14	-0.15	0.51	0.13	-0.27	-0.21
5 New hires, median	1979	2006		0.037	1.07	0.79	-0.22	-0.24	0.04	0.24	-0.42	-0.35
6	1984	2006		0.036	1.36	0.84	-0.12	-0.17	0.16	0.22	-0.40	-0.33
7 All matched workers, mean	1979	2006	0.57	0.015	0.50	0.84	0.25	0.15	0.20	-0.20	-0.02	0.08
8	1984	2006	0.57	0.015	0.65	0.84	0.22	0.09	0.16	-0.09	-0.12	-0.03
9 Job stayers, mean	1979	2006		0.016	0.51	0.82	0.28	0.16	0.22	-0.21	0.01	0.10
10	1984	2006		0.016	0.67	0.81	0.23	0.09	0.17	-0.09	-0.10	-0.02
11 New hires, mean	1979	2006		0.032	0.81	0.75	-0.20	-0.18	-0.02	0.15	-0.38	-0.29
12	1984	2006		0.031	0.99	0.69	-0.06	-0.09	0.10	0.09	-0.33	-0.24

All moments have been corrected for sampling error in the CPS wage series, see appendix C for details.

Table 4: Business cycle statistics (logs, HP filtered, $\lambda = 1,600$).

Table 4. Business cycle statistics (HP filtered, smoothing parameter 1600)

	sample period		correlation aggregate wage	standard deviation	relative standard deviation	auto-correlation	correlation output	hours	labor productiv.	unempl	vacancies	labor market tightn.
Aggregate wage												
1	1947	2006	1.00	0.009	0.41	0.78	0.23	0.05	0.40	-0.08	0.26	0.25
2	1951	2001	1.00	0.009	0.41	0.79	0.27	0.10	0.38	-0.18	0.27	0.26
3	1979	2006	1.00	0.010	0.53	0.81	0.01	-0.19	0.39	0.10	-0.02	-0.06
4	1979	2006	1.00	0.010	0.56	0.81	-0.04	-0.26	0.39	0.15	-0.07	-0.11
5	1984	2006	1.00	0.011	0.83	0.82	-0.02	-0.30	0.56	0.18	-0.07	-0.12
CPS wage for all workers												
1 Median, hours weighted, all sectors	1979	2006	0.08	0.011	0.53	0.68	-0.12	-0.08	-0.10	0.10	-0.17	-0.14
2	1984	2006	0.08	0.011	0.70	0.67	-0.13	-0.09	-0.05	0.11	-0.23	-0.18
3 Median, hours weighted, private nfm	1979	2006	0.41	0.012	0.53	0.55	-0.27	-0.37	0.12	0.39	-0.38	-0.39
4	1984	2006	0.41	0.012	0.73	0.57	-0.24	-0.37	0.31	0.41	-0.40	-0.41
5 Median, hours weighted, private nfm, non-superv.	1979	2006	0.45	0.012	0.54	0.69	0.13	0.07	0.14	-0.12	0.14	0.13
6	1984	2006	0.45	0.013	0.77	0.71	0.13	0.00	0.23	-0.08	0.11	0.09
7 Median, private nfm, non-superv.	1979	2006	0.23	0.013	0.60	0.58	0.10	0.00	0.20	-0.01	0.01	0.01
8	1984	2006	0.23	0.012	0.76	0.51	0.02	-0.09	0.21	0.11	-0.09	-0.10
9 Mean, hours weighted, private nfm, non-superv.	1979	2006	0.28	0.009	0.41	0.53	-0.03	-0.05	0.02	0.08	-0.11	-0.10
10	1984	2006	0.28	0.010	0.57	0.55	0.03	-0.04	0.12	0.08	-0.09	-0.09
11 Mean, private nfm, non-superv.	1979	2006	0.26	0.009	0.42	0.55	0.00	0.00	0.01	0.03	-0.07	-0.05
12	1984	2006	0.26	0.010	0.59	0.57	0.06	0.01	0.10	0.03	-0.06	-0.04
CPS wage (hours weighted, private nfm, non-superv.)												
1 All matched workers, median	1979	2006	0.40	0.013	0.57	0.76	0.11	0.01	0.20	0.01	0.08	0.04
2	1984	2006	0.40	0.014	0.81	0.81	0.16	0.00	0.29	0.03	0.09	0.04
3 Job stayers, median	1979	2006		0.014	0.60	0.61	-0.09	-0.21	0.19	0.25	-0.18	-0.21
4	1984	2006		0.014	0.83	0.61	-0.03	-0.23	0.42	0.29	-0.17	-0.23
5 New hires, median	1979	2006		0.031	1.06	0.46	-0.47	-0.46	-0.13	0.44	-0.54	-0.50
6	1984	2006		0.029	1.33	0.45	-0.32	-0.36	0.15	0.35	-0.49	-0.44
7 All matched workers, mean	1979	2006	0.28	0.010	0.42	0.46	-0.04	-0.05	0.00	0.09	-0.09	-0.09
8	1984	2006	0.28	0.010	0.58	0.49	0.02	-0.03	0.09	0.08	-0.05	-0.06
9 Job stayers, mean	1979	2006		0.010	0.44	0.43	0.00	-0.02	0.04	0.06	-0.04	-0.05
10	1984	2006		0.011	0.61	0.45	0.04	-0.02	0.10	0.08	-0.03	-0.05
11 New hires, mean	1979	2006		0.031	0.68	0.21	-0.46	-0.40	-0.19	0.37	-0.51	-0.46
12	1984	2006		0.030	0.87	-0.03	-0.19	-0.22	0.09	0.16	-0.37	-0.28

All moments have been corrected for sampling error in the CPS wage series, see appendix C for details.

Table 5: Business cycle statistics (logs, bandpass filtered, periods 6–32 quarters).

Table 5. Business cycle statistics (bandpass filtered, periods 6 to 32 quarters)

	sample period		correlation aggregate wage	standard deviation	relative standard deviation	auto-correlation	correlation: output	correlation: hours	correlation: labor productiv.	correlation: unempl	correlation: vacancies	correlation: labor market tightn.
Aggregate wage												
1	1947	2006	1.00	0.009	0.42	0.92	0.27	0.06	0.49	-0.07	0.34	0.30
2	1951	2001	1.00	0.009	0.41	0.92	0.33	0.13	0.48	-0.18	0.33	0.29
3	1979	2006	1.00	0.010	0.59	0.92	0.10	-0.14	0.48	0.05	0.10	0.04
4	1979	2006	1.00	0.010	0.64	0.92	0.04	-0.25	0.46	0.08	0.06	0.00
5	1984	2006	1.00	0.010	0.86	0.92	0.12	-0.26	0.65	0.07	0.12	0.03
CPS wage for all workers												
1 Median, hours weighted, all sectors	1979	2006	-0.15	0.008	0.51	0.84	-0.27	-0.17	-0.23	0.21	-0.26	-0.24
2	1984	2006	-0.15	0.007	0.58	0.86	-0.22	-0.14	-0.14	0.19	-0.23	-0.21
3 Median, hours weighted, private nfm	1979	2006	0.38	0.007	0.49	0.86	-0.30	-0.48	0.18	0.48	-0.38	-0.43
4	1984	2006	0.38	0.007	0.59	0.86	-0.25	-0.49	0.41	0.51	-0.35	-0.43
5 Median, hours weighted, private nfm, non-superv.	1979	2006	0.43	0.009	0.58	0.86	0.16	0.13	0.09	-0.21	0.26	0.24
6	1984	2006	0.43	0.009	0.77	0.86	0.27	0.15	0.22	-0.25	0.34	0.30
7 Median, private nfm, non-superv.	1979	2006	0.19	0.009	0.57	0.82	0.01	-0.05	0.08	0.01	-0.02	-0.02
8	1984	2006	0.19	0.008	0.63	0.80	0.07	-0.03	0.17	0.05	0.03	-0.01
9 Mean, hours weighted, private nfm, non-superv.	1979	2006	0.17	0.005	0.37	0.88	-0.07	-0.03	-0.08	0.05	-0.01	-0.02
10	1984	2006	0.17	0.005	0.45	0.88	0.10	0.07	0.05	-0.02	0.16	0.10
11 Mean, private nfm, non-superv.	1979	2006	0.15	0.006	0.38	0.88	0.00	0.05	-0.09	-0.05	0.07	0.06
12	1984	2006	0.15	0.006	0.47	0.88	0.16	0.16	0.02	-0.11	0.23	0.18
CPS wage (hours weighted, private nfm, non-superv.)												
1 All matched workers, median	1979	2006	0.39	0.009	0.62	0.91	0.19	0.11	0.18	-0.11	0.24	0.18
2	1984	2006	0.39	0.010	0.83	0.92	0.31	0.15	0.29	-0.16	0.33	0.26
3 Job stayers, median	1979	2006		0.010	0.65	0.89	-0.07	-0.29	0.32	0.30	-0.16	-0.23
4	1984	2006		0.010	0.80	0.90	0.03	-0.32	0.60	0.34	-0.13	-0.23
5 New hires, median	1979	2006		0.013	0.89	0.84	-0.48	-0.39	-0.31	0.40	-0.42	-0.41
6	1984	2006		0.012	1.00	0.89	-0.30	-0.24	-0.13	0.24	-0.24	-0.24
7 All matched workers, mean	1979	2006	0.21	0.006	0.38	0.89	-0.09	-0.05	-0.09	0.06	-0.01	-0.03
8	1984	2006	0.21	0.006	0.47	0.89	0.09	0.07	0.04	-0.02	0.18	0.11
9 Job stayers, mean	1979	2006		0.006	0.40	0.89	-0.02	-0.01	-0.02	0.03	0.04	0.01
10	1984	2006		0.006	0.49	0.90	0.11	0.07	0.07	-0.01	0.18	0.11
11 New hires, mean	1979	2006		0.010	0.63	0.76	-0.46	-0.33	-0.35	0.31	-0.35	-0.34
12	1984	2006		0.007	0.60	0.81	-0.23	-0.13	-0.20	0.06	-0.09	-0.08

Table 6: Business cycle statistics (logs, first differences.

Table 6. Business cycle statistics (first differences)

	sample period		correlation aggregate wage	standard deviation	relative standard deviation	auto-correlation	correlation: output	correlation: hours	correlation: labor productiv.	correlation: unempl	correlation: vacancies	correlation: labor market tightn.
Aggregate wage												
1	1947	2006	1.00	0.007	0.49	0.17	0.20	-0.07	0.35	-0.10	0.21	0.20
2	1951	2001	1.00	0.006	0.49	0.17	0.21	-0.06	0.37	-0.13	0.20	0.20
3	1979	2006	1.00	0.006	0.68	0.20	-0.03	-0.30	0.27	0.10	0.04	-0.02
4	1979	2006	1.00	0.006	0.68	0.21	-0.02	-0.30	0.28	0.10	0.05	-0.02
5	1984	2006	1.00	0.007	1.03	0.21	0.02	-0.32	0.35	0.15	0.08	-0.02
CPS wage for all workers												
1 Median, hours weighted, all sectors	1979	2006	0.11	0.013	0.81	-0.12	-0.03	-0.02	-0.03	0.09	-0.09	-0.10
2	1984	2006	0.11	0.013	1.15	-0.20	-0.06	-0.04	-0.02	0.13	-0.16	-0.16
3 Median, hours weighted, private nfm	1979	2006	0.11	0.014	0.95	-0.52	-0.10	-0.17	0.04	0.25	-0.18	-0.22
4	1984	2006	0.11	0.014	1.36	-0.52	0.01	-0.09	0.10	0.21	-0.13	-0.18
5 Median, hours weighted, private nfm, non-superv.	1979	2006	0.38	0.015	0.81	-0.37	0.05	0.00	0.07	-0.03	0.00	0.02
6	1984	2006	0.38	0.015	1.19	-0.44	0.06	-0.02	0.09	-0.05	0.01	0.03
7 Median, private nfm, non-superv.	1979	2006	0.04	0.015	1.03	-0.34	0.18	0.07	0.18	-0.01	0.00	0.00
8	1984	2006	0.04	0.015	1.46	-0.47	0.07	-0.02	0.10	0.10	-0.10	-0.10
9 Mean, hours weighted, private nfm, non-superv.	1979	2006	0.10	0.012	0.75	-0.69	0.14	0.11	0.08	0.07	-0.03	-0.05
10	1984	2006	0.10	0.012	1.09	-0.72	0.18	0.07	0.12	0.12	-0.04	-0.08
11 Mean, private nfm, non-superv.	1979	2006	0.10	0.012	0.76	-0.60	0.17	0.11	0.12	0.05	-0.02	-0.04
12	1984	2006	0.10	0.012	1.12	-0.64	0.20	0.06	0.15	0.10	-0.04	-0.07
CPS wage (hours weighted, private nfm, non-superv.)												
1 All matched workers, median	1979	2006	0.29	0.017	0.75	-0.56	0.06	-0.08	0.17	0.09	0.05	-0.01
2	1984	2006	0.29	0.017	1.09	-0.56	0.04	-0.09	0.14	0.17	0.02	-0.07
3 Job stayers, median	1979	2006		0.017	1.00	-0.62	-0.04	0.01	-0.07	0.12	-0.05	-0.09
4	1984	2006		0.017	1.47	-0.72	-0.03	0.04	-0.07	0.15	0.00	-0.07
5 New hires, median	1979	2006		0.043	2.00	-0.70	-0.16	-0.31	0.10	0.09	-0.27	-0.20
6	1984	2006		0.040	2.65	-1.04	0.14	-0.11	0.27	-0.07	-0.25	-0.12
7 All matched workers, mean	1979	2006	0.14	0.013	0.82	-0.71	0.13	0.10	0.08	0.05	0.00	-0.02
8	1984	2006	0.14	0.013	1.19	-0.77	0.16	0.07	0.10	0.09	0.00	-0.04
9 Job stayers, mean	1979	2006		0.014	0.88	-0.70	0.13	0.13	0.05	0.03	0.06	0.02
10	1984	2006		0.014	1.30	-0.73	0.11	0.08	0.03	0.09	0.05	-0.01
11 New hires, mean	1979	2006		0.045	1.63	-1.14	-0.04	-0.23	0.18	0.09	-0.22	-0.17
12	1984	2006		0.045	2.33	-1.34	0.23	-0.11	0.37	-0.02	-0.19	-0.10

All moments have been corrected for sampling error in the CPS wage series, see appendix C for details.

Table 7: Wage elasticities for all workers and new hires, CPS

Table 7. Wage elasticities for all workers and new hires, CPS

	Aggregate wage				Wages from the Current Population Survey, OLS								Wages from the Current Population Survey, WLS							
					Mean wage				Median wage				Mean wage				Median wage			
					All workers		New hires		All workers		New hires		All workers		New hires		All workers		New hires	
	1947-2006	1951-2001	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006
Labor productivity	0.248	0.2714	0.2676	0.4253	0.1072	0.1677	0.4246	0.9392	0.184	0.1919	0.2685	0.6433	0.126	0.2508	0.0198	0.9156	0.2915	0.3711	0.381	0.7276
	[0.0432]	[0.0486]	[0.0853]	[0.1086]	[0.1161]	[0.1403]	[0.3735]	[0.4405]	[0.1803]	[0.2406]	[0.4113]	[0.3893]	[0.1480]	[0.2034]	[0.3784]	[0.4489]	[0.1986]	[0.2441]	[0.3438]	[0.3439]
	236	204	108	89	102	83	100	81	102	83	98	79	102	83	100	81	102	83	98	79
SBP, educ only					0.1484	0.2067	0.4549	0.9343	0.1891	0.1608	0.3789	0.7469	0.166	0.2882	0.0582	0.8122	0.3587	0.4476	0.4344	0.6976
					[0.1198]	[0.1417]	[0.3536]	[0.4373]	[0.1798]	[0.2345]	[0.4090]	[0.3999]	[0.1654]	[0.2048]	[0.3574]	[0.5181]	[0.2007]	[0.2444]	[0.3317]	[0.3743]
					100	81	98	79	100	81	98	79	100	81	98	79	100	81	98	79
SBP, educ and demogr					0.1644	0.2419	0.4227	0.9049	0.2051	0.196	0.3634	0.7421	0.1673	0.316	0.005	0.7159	0.3952	0.4968	0.3871	0.6203
					[0.1217]	[0.1373]	[0.3359]	[0.4105]	[0.1790]	[0.2301]	[0.4045]	[0.4070]	[0.1729]	[0.2011]	[0.3519]	[0.4930]	[0.2019]	[0.2438]	[0.3406]	[0.4221]
					100	81	98	79	100	81	98	79	100	81	98	79	100	81	98	79
Industry weights							0.2973	0.733			0.141	0.4657			-0.0606	0.6293			0.1394	0.4098
							[0.3976]	[0.4754]			[0.3073]	[0.4159]			[0.4387]	[0.5231]			[0.3650]	[0.4713]
							100	81			98	79			100	81			98	79
Unemployment rate	-0.1531	-0.1706	0.2675	0.6284	0.1368	0.429	0.5996	-0.0652	0.2138	0.5576	0.7317	-0.8798	-0.062	0.5038	0.7987	0.1991	0.3717	0.7727	0.956	0.0345
	[0.1095]	[0.1150]	[0.2085]	[0.3320]	[0.3345]	[0.4929]	[0.8785]	[1.2155]	[0.3657]	[0.5812]	[1.0120]	[1.1266]	[0.3767]	[0.6189]	[0.9192]	[1.2793]	[0.4153]	[0.5870]	[0.8445]	[1.3470]
	232	204	108	89	102	83	100	81	102	83	98	79	102	83	100	81	102	83	98	79
SBP, educ only					-0.0955	0.253	0.1433	-1.1074	-0.0488	0.3138	0.3373	-1.6512	-0.2941	0.3694	0.5163	-0.8529	0.0578	0.4619	0.4531	-0.9545
					[0.3471]	[0.4895]	[0.8972]	[1.2346]	[0.3956]	[0.6146]	[1.0283]	[1.1321]	[0.3992]	[0.6120]	[0.9188]	[1.2955]	[0.4559]	[0.6773]	[0.8435]	[1.2952]
					100	81	98	79	100	81	98	79	100	81	98	79	100	81	98	79
SBP, educ and demogr					-0.088	0.1768	-0.0274	-1.3037	-0.0413	0.2375	0.1318	-1.9394	-0.2718	0.2938	0.3501	-1.0528	0.0084	0.3498	0.2287	-1.3203
					[0.3515]	[0.4887]	[0.8477]	[1.1476]	[0.4018]	[0.6205]	[0.9843]	[1.0966]	[0.4179]	[0.6086]	[0.8940]	[1.2274]	[0.4615]	[0.6951]	[0.8146]	[1.2845]
					100	81	98	79	100	81	98	79	100	81	98	79	100	81	98	79
Industry weights							-0.2434	-0.4331			0.2372	0.3115			-0.2806	-0.181			0.2999	1.0122
							[0.7495]	[1.0524]			[0.6979]	[1.3253]			[0.8708]	[1.3075]			[0.6841]	[1.5927]
							100	81			98	79			100	81			98	79

Coefficient estimates, standard errors in brackets, number of observations (quarters). All regressions include quarter dummies. First step estimates are weighted by ORG sampling weights and hours worked. Second step WLS estimates are weighted by the inverse of the variance of the first step estimates.

Table 8: Wage elasticities for all workers and job stayers, PSID

Table 8. Wage elasticities for all workers, job stayers and job changers, PSID

Estimation procedure / Control variables	2-step estimates first step in first diffs experience and job tenure		2-step estimates first step in first diffs -		1-step estimates clustered standard errors -		2-step estimates first step in levels -		2-step estimates first step in levels education and demogr	
	stayers	all	stayers	all	stayers	all	stayers	all	stayers	all
Unemployment rate	-0.8094	-1.0104	-0.8321	-1.0103	-0.8321	-1.0103	-0.3689	-0.6276	-0.7995	-0.8009
	[0.1977]	[0.2101]	[0.1943]	[0.2037]	[0.1892]	[0.1908]	[0.6220]	[0.2175]	[0.1963]	[0.2196]
	42164	52525	42164	52525	42164	52525	42164	52525	42164	52525
	21	21	21	21			21	21	21	21
Labor productivity	0.399	0.4319	0.3609	0.4003	0.3609	0.4003	0.6657	0.423	0.2633	0.3736
	[0.1835]	[0.2093]	[0.1890]	[0.2093]	[0.1647]	[0.1921]	[0.5211]	[0.1916]	[0.1907]	[0.1967]
	42164	52525	42164	52525	42164	52525	42164	52525	42164	52525
	21	21	21	21			21	21	21	21
Labor productivity (no time trend)	0.4339	0.4994	0.403	0.4858	0.403	0.4858	0.8423	0.5413	0.3618	0.4943
	[0.1991]	[0.2281]	[0.2127]	[0.2428]	[0.1936]	[0.2369]	[0.6690]	[0.2473]	[0.2284]	[0.2643]
	42164	52525	42164	52525	42164	52525	42164	52525	42164	52525
	21	21	21	21			21	21	21	21

Coefficient estimates, standard errors in brackets, number of observations (years) for 1st step and 2nd step. All workers excludes self-employed. Job stayers includes multiple job holders. The first two panels include a linear time trend, the third panel does not. The sample period is 1970-1991 in all regressions. Data are from Devereux (2001).

Table 9: Wage elasticities for all workers and new hires, CPS, men only

Table 9. Wage elasticities for all workers and new hires, CPS, men only

	Aggregate wage				Wages from the Current Population Survey, OLS								Wages from the Current Population Survey, WLS							
					Mean wage				Median wage				Mean wage				Median wage			
					All workers		New hires		All workers		New hires		All workers		New hires		All workers		New hires	
	1947-2006	1951-2001	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006
Labor productivity	0.248 [0.0432] 236	0.2714 [0.0486] 204	0.2676 [0.0853] 108	0.4253 [0.1086] 89	0.0912 [0.1435] 102	0.1937 [0.1658] 83	0.6243 [0.4417] 102	1.415 [0.5046] 83	0.192 [0.2377] 102	0.4715 [0.2804] 83	0.6438 [0.5703] 100	1.5828 [0.6275] 81	0.1005 [0.1772] 102	0.3432 [0.2349] 83	-0.1408 [0.4509] 102	1.3868 [0.5143] 83	0.1265 [0.2926] 102	0.408 [0.3289] 83	0.5122 [0.5431] 100	1.4418 [0.6336] 81
SBP, educ only					0.1342 [0.1470] 100	0.26 [0.1616] 81	0.6283 [0.4628] 100	1.5285 [0.5248] 81	0.2043 [0.2380] 100	0.4974 [0.2834] 81	0.5905 [0.5727] 98	1.6043 [0.5927] 79	0.1218 [0.1914] 100	0.4143 [0.2363] 81	-0.2054 [0.4578] 100	1.5332 [0.5878] 81	0.1878 [0.2932] 100	0.5337 [0.2998] 81	0.4671 [0.5447] 98	1.4887 [0.5927] 79
SBP, educ and demogr					0.1176 [0.1463] 100	0.2294 [0.1646] 81	0.583 [0.4550] 100	1.3847 [0.5186] 81	0.1877 [0.2330] 100	0.4668 [0.2745] 81	0.5727 [0.5560] 98	1.5032 [0.5754] 79	0.1204 [0.1932] 100	0.3999 [0.2378] 81	-0.1857 [0.4696] 100	1.3386 [0.5901] 81	0.1829 [0.2892] 100	0.5404 [0.2835] 81	0.4726 [0.5258] 98	1.4108 [0.5765] 79
Industry weights							0.7407 [0.5687] 102	1.3861 [0.6770] 83			0.9557 [0.7527] 100	1.7815 [0.9592] 81			0.0995 [0.6599] 102	1.3206 [0.7450] 83			0.7824 [0.7076] 100	1.4667 [0.9995] 81
Unemployment rate	-0.1531 [0.1095] 232	-0.1706 [0.1150] 204	0.2675 [0.2085] 108	0.6284 [0.3320] 89	0.0613 [0.3950] 102	0.1885 [0.5280] 83	0.9749 [0.9140] 102	0.7085 [1.2955] 83	-0.146 [0.5425] 102	0.4442 [0.8720] 83	1.6175 [0.9782] 100	1.8968 [1.7282] 81	-0.0366 [0.4442] 102	0.3316 [0.6497] 83	1.3076 [1.0255] 102	1.0315 [1.3742] 83	-0.5549 [0.4650] 102	-0.304 [0.8171] 83	1.4241 [0.9392] 100	1.2834 [1.6839] 81
SBP, educ only					-0.1349 [0.4013] 100	0.0865 [0.5200] 81	0.6853 [0.8830] 100	-0.0994 [1.3364] 81	-0.3859 [0.5436] 100	0.2439 [0.8799] 81	1.2776 [1.0383] 98	0.9201 [1.8578] 79	-0.2518 [0.4489] 100	0.2393 [0.6239] 81	1.1382 [0.9516] 100	0.2349 [1.5669] 81	-0.7208 [0.4653] 100	-0.5187 [0.8274] 81	1.1307 [1.0134] 98	0.3962 [1.8096] 79
SBP, educ and demogr					-0.1915 [0.3950] 100	-0.0213 [0.5323] 81	0.3915 [0.8886] 100	-0.4232 [1.3093] 81	-0.4425 [0.5364] 100	0.1361 [0.8863] 81	0.9733 [1.0312] 98	0.5839 [1.8337] 79	-0.3004 [0.4448] 100	0.1215 [0.6273] 81	0.8327 [0.9626] 100	-0.1478 [1.5338] 81	-0.7525 [0.4625] 100	-0.6483 [0.8339] 81	0.7954 [1.0003] 98	0.0171 [1.7780] 79
Industry weights							-0.6122 [0.9974] 102	-0.4803 [1.2971] 83			-0.107 [1.3172] 100	0.2777 [2.1227] 81			-0.4733 [1.2468] 102	0.2975 [1.2547] 83			-0.2842 [1.2635] 100	-0.1256 [2.1428] 81

Coefficient estimates, standard errors in brackets, number of observations (quarters). All regressions include quarter dummies. First step estimates are weighted by ORG sampling weights and hours worked. Second step WLS estimates are weighted by the inverse of the variance of the first step estimates.

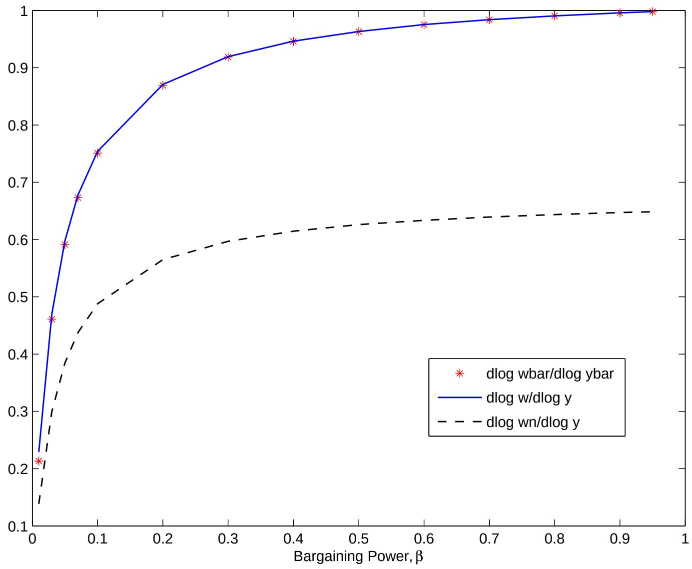
Table 10: Wage elasticities for all workers and new hires with respect to different productivity measures, CPS

Table 10. Wage elasticities with respect to different productivity measures, CPS

	Aggregate wage				Wages from the Current Population Survey, OLS								Wages from the Current Population Survey, WLS							
					Mean wage				Median wage				Mean wage				Median wage			
					All workers		New hires		All workers		New hires		All workers		New hires		All workers		New hires	
	1947-2006	1951-2001	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006	1979-2006	1984-2006
Total Factor Productivity	0.2012 [0.0409] 236	0.2181 [0.0456] 204	0.1667 [0.0854] 108	0.3771 [0.1245] 89	0.1372 [0.1209] 102	0.2338 [0.1718] 83	0.2302 [0.3839] 100	1.0168 [0.5091] 81	0.1463 [0.1715] 102	0.1841 [0.2643] 83	-0.0138 [0.4563] 98	0.6462 [0.4162] 79	0.1442 [0.1390] 102	0.3248 [0.2399] 83	-0.1819 [0.3445] 100	0.8403 [0.5417] 81	0.2051 [0.1787] 102	0.2834 [0.2470] 83	0.107 [0.3607] 98	0.6646 [0.3799] 79
SBP, educ only					0.1923 [0.1228] 100	0.2853 [0.1654] 81	0.2829 [0.3635] 98	1.0391 [0.4972] 79	0.1739 [0.1718] 100	0.1665 [0.2530] 81	0.1252 [0.4589] 98	0.8234 [0.4319] 79	0.1979 [0.1543] 100	0.3643 [0.2212] 81	-0.1273 [0.3252] 98	0.7611 [0.6061] 79	0.2827 [0.1818] 100	0.3736 [0.2489] 81	0.1946 [0.3447] 98	0.6821 [0.4090] 79
SBP, educ and demogr					0.2048 [0.1253] 100	0.329 [0.1592] 81	0.2757 [0.3380] 98	1.0199 [0.4631] 79	0.1864 [0.1721] 100	0.2102 [0.2485] 81	0.137 [0.4434] 98	0.8437 [0.4465] 79	0.1967 [0.1618] 100	0.403 [0.2143] 81	-0.1433 [0.3125] 98	0.6798 [0.5715] 79	0.3189 [0.1822] 100	0.4322 [0.2471] 81	0.1758 [0.3420] 98	0.622 [0.4638] 79
Industry weights							0.2165 [0.3853] 100	0.7807 [0.5323] 81			0.0642 [0.2934] 98	0.5026 [0.4526] 79			-0.0778 [0.4062] 100	0.5386 [0.5860] 81			0.0966 [0.3362] 98	0.4273 [0.5305] 79
Identified technology shocks			0.2486 [0.0626] 106	0.3001 [0.0704] 89	-0.0157 [0.0875] 100	0.0366 [0.0921] 83	0.3969 [0.2760] 98	0.6108 [0.2991] 81	0.141 [0.1215] 100	0.17 [0.1307] 83	0.5552 [0.2791] 96	0.6279 [0.2958] 79	-0.0916 [0.1076] 100	0.0344 [0.1181] 83	-0.0146 [0.3408] 98	0.6695 [0.3149] 81	0.2085 [0.1333] 100	0.2731 [0.1401] 83	0.6126 [0.2594] 96	0.7064 [0.2732] 79
SBP, educ only					0.0098 [0.0891] 98	0.0743 [0.0944] 81	0.4207 [0.2725] 96	0.6319 [0.2996] 79	0.1349 [0.1193] 98	0.1633 [0.1273] 81	0.6253 [0.2750] 96	0.6973 [0.2891] 79	-0.0828 [0.1088] 98	0.0804 [0.1196] 81	0.0055 [0.3312] 96	0.6775 [0.3317] 79	0.2857 [0.1430] 98	0.3638 [0.1495] 81	0.6471 [0.2611] 96	0.7202 [0.2740] 79
SBP, educ and demogr					0.0281 [0.0883] 98	0.0965 [0.0927] 81	0.4041 [0.2623] 96	0.6262 [0.2856] 79	0.1531 [0.1185] 98	0.1856 [0.1258] 81	0.6146 [0.2726] 96	0.6962 [0.2848] 79	-0.0711 [0.1095] 98	0.0988 [0.1155] 81	-0.0199 [0.3200] 96	0.6657 [0.3239] 79	0.3169 [0.1440] 98	0.3999 [0.1501] 81	0.6106 [0.2668] 96	0.6798 [0.2866] 79
Industry weights							0.2351 [0.2874] 98	0.5128 [0.3045] 81			0.1249 [0.2369] 96	0.2457 [0.2721] 79			-0.243 [0.3447] 98	0.5429 [0.3217] 81			0.0856 [0.2667] 96	0.2173 [0.3051] 79

Coefficient estimates, standard errors in brackets, number of observations (quarters). All regressions include quarter dummies. First step estimates are weighted by ORG sampling weights and hours worked. Second step WLS estimates are weighted by the inverse of the variance of the first step estimates.

Figure 1: The elasticity of permanet wage, $\bar{w}$, with respect to permanent productivity, $\bar{y}$



Parameters for the calibration are as in Shimer (2005). The vacancy posting cost is chosen to yield steady state tightness of unity. The reported elasticity is an average over 100 simulations of length 89.

Figure 2: The effect of the autoregressive coefficient on $\frac{\mathrm{d}\log\bar{y}}{\mathrm{d}\log y}$.

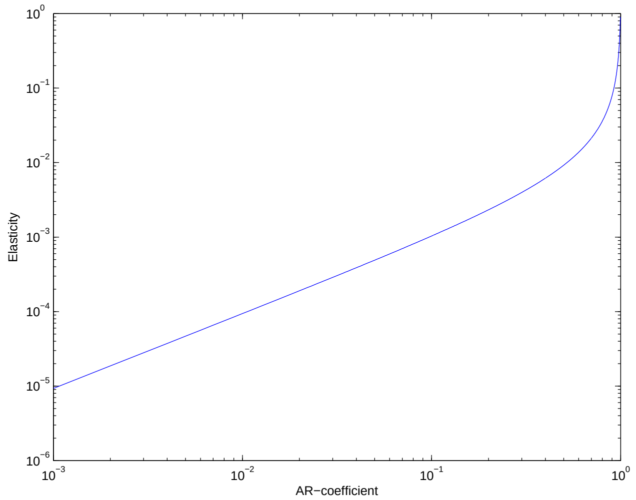
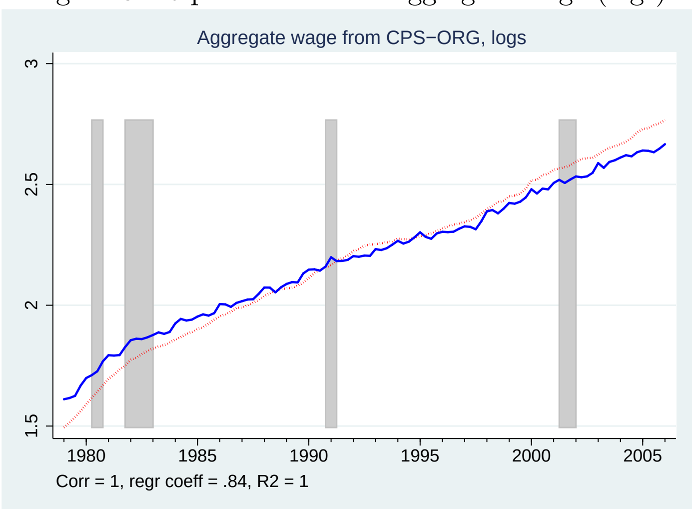


Figure 3: Replication of the aggregate wage (logs)



Solid blue line: hours-weighted median (nominal) wage of non-supervisory workers in the private, non-farm sector from the CPS-ORG. Dotted red line: aggregate (nominal) hourly compensation in the private non-farm sector from the BLS productivity and costs program. Because hourly compensation is an index, we set the sample mean equal to the sample mean of the CPS series.

Figure 4: Replication of the aggregate wage (logs, HP filtered, $\lambda = 100,000$)

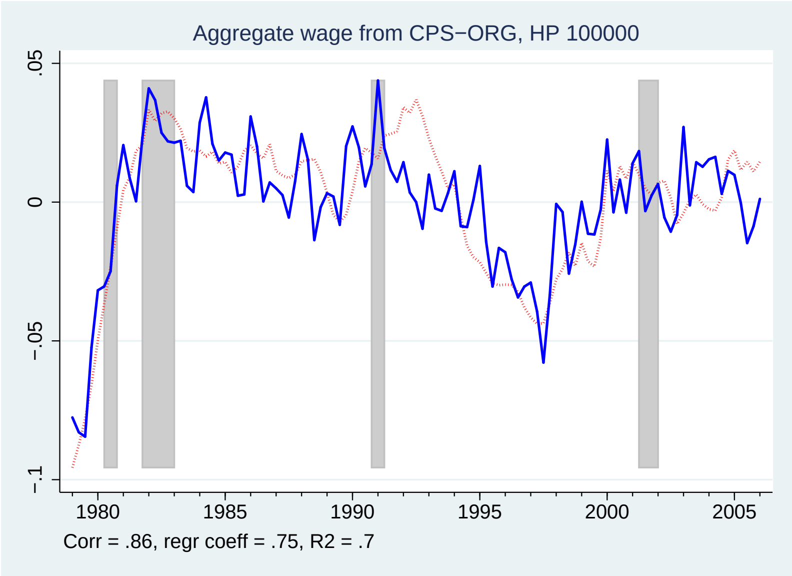


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Figure 5: Replication of the aggregate wage (logs, HP filtered, $\lambda = 1600$)

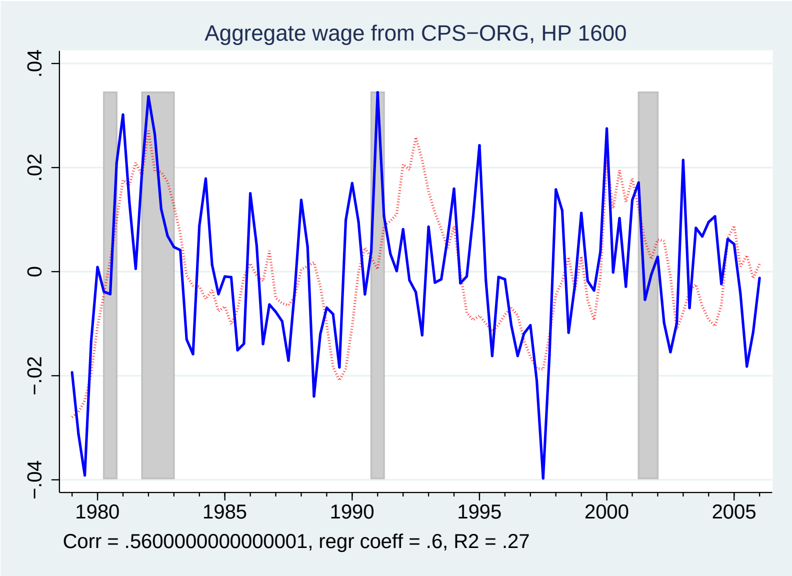


Figure 6: Replication of the aggregate wage (logs, BP filtered, 6-32 qrt).

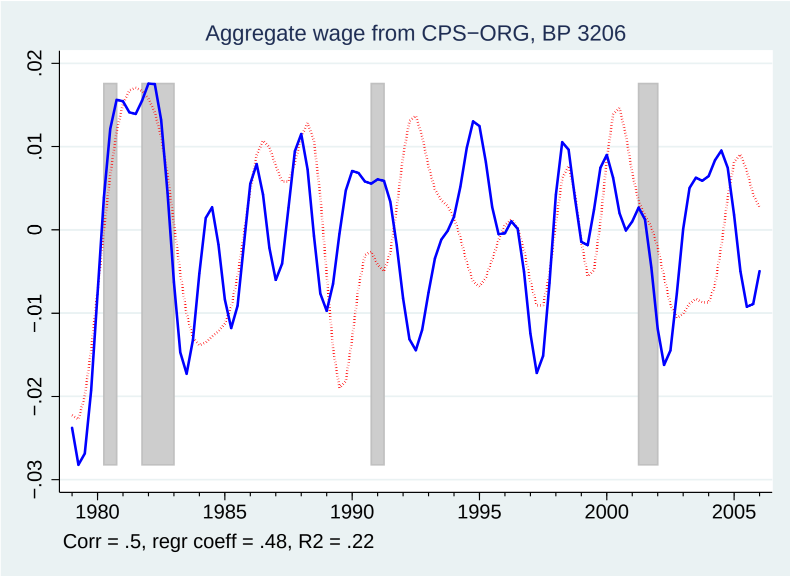


Figure 7: Replication of the aggregate wage (logs, first differences).

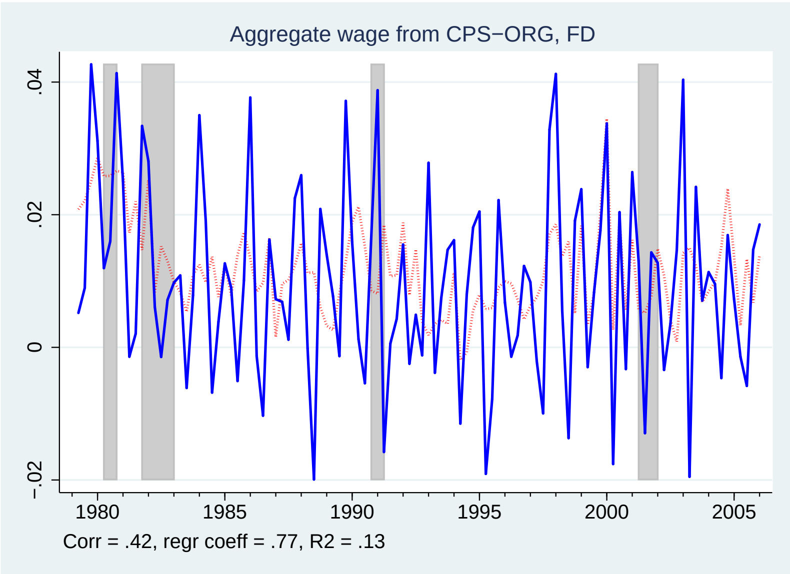


Figure 8: Wage of workers in ongoing jobs

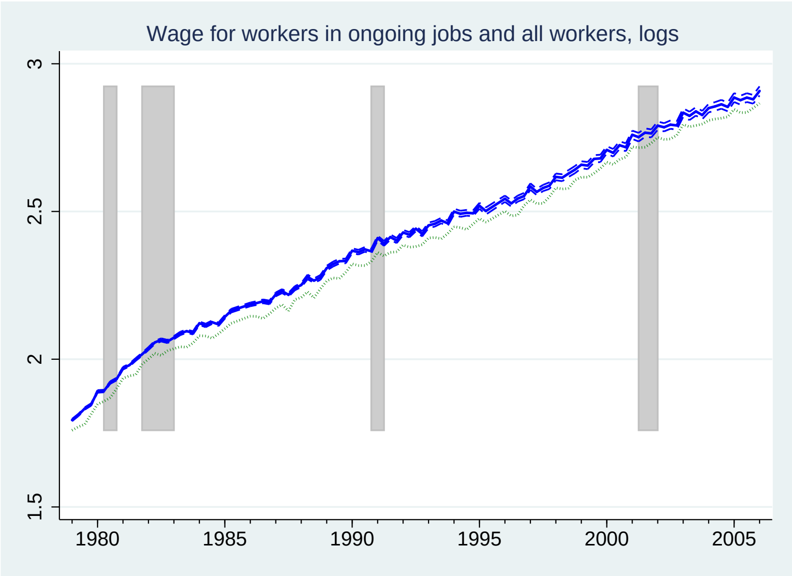


Figure 9: Wage of newly hired workers

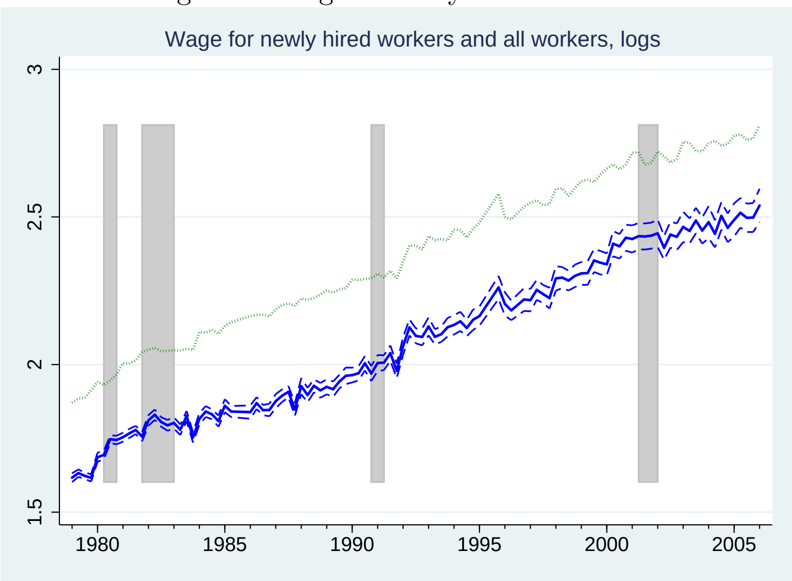


Figure 10: Wage cyclicality for workers in ongoing jobs.

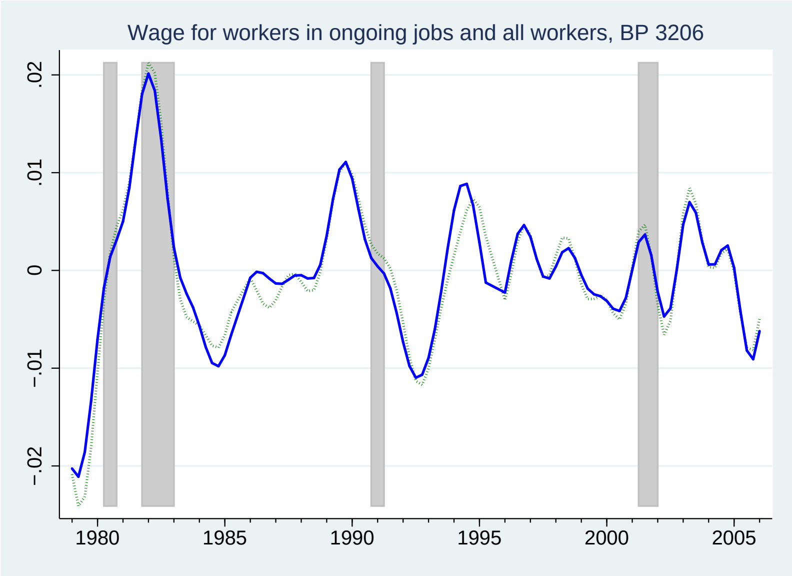


Figure 11: Wage cyclicality for newly hired workers.

Figure 12: Wage cyclicality for newly hired workers, corrected for composition bias.

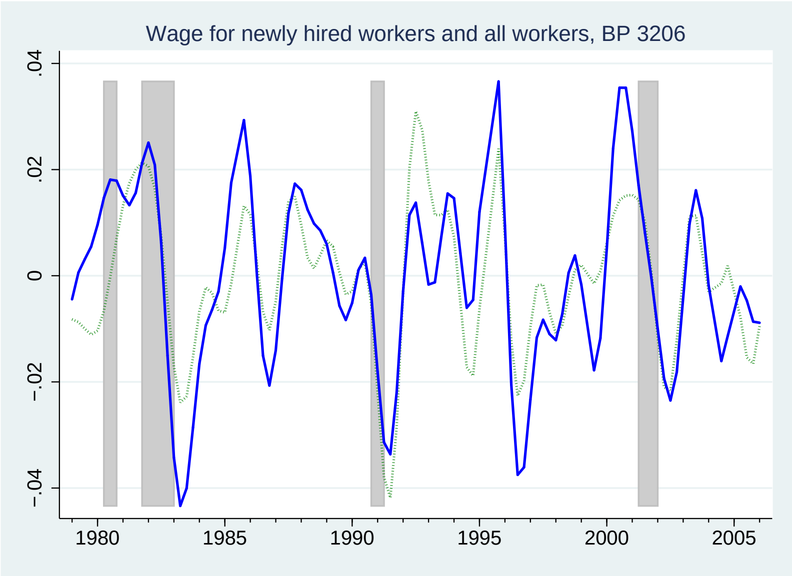
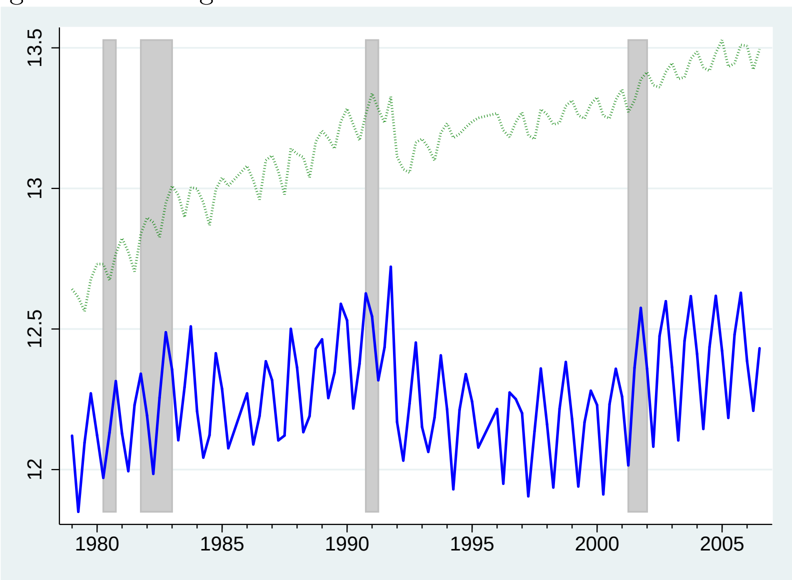


Figure 13: Average education level for new hires and all workers.



The discrete change in 1992 is due to a change in coding of the education variables in the CPS.

Figure 14: Average labor market experience for new hires and all workers.

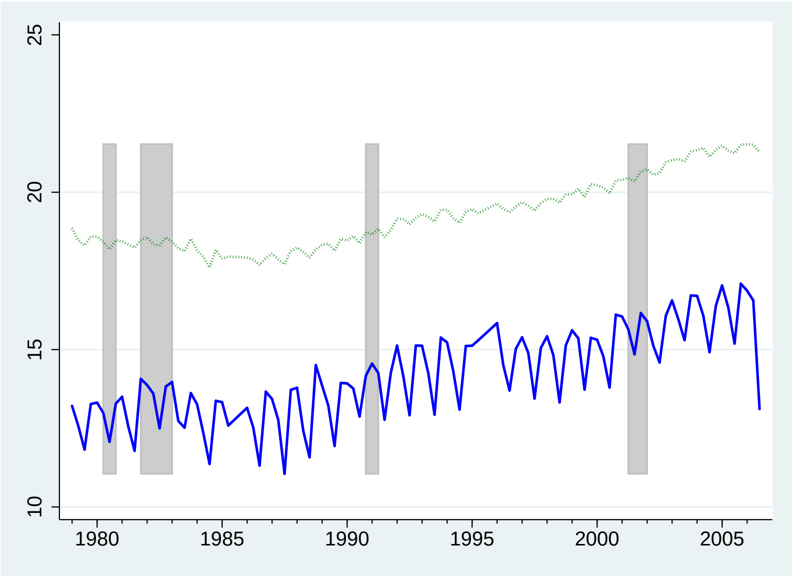


Figure 15: Fraction of females among new hires and all workers.

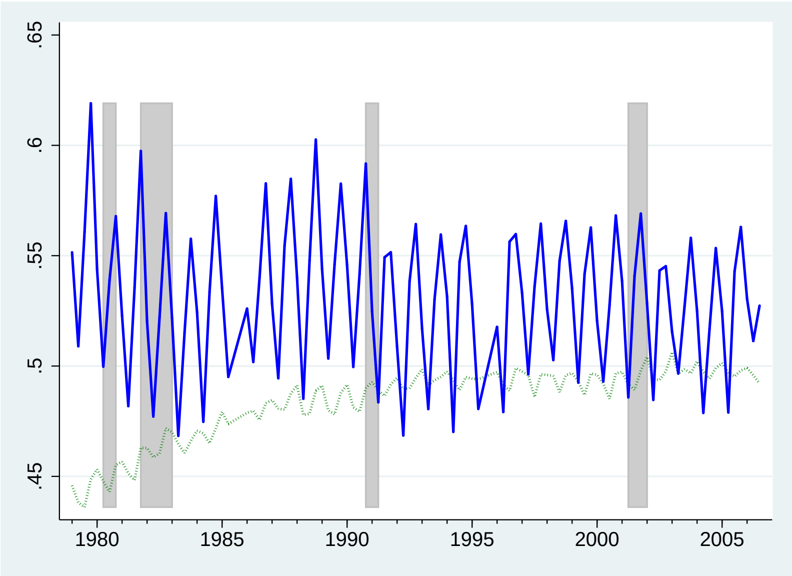


Figure 16: Fraction of blacks among new hires and all workers.

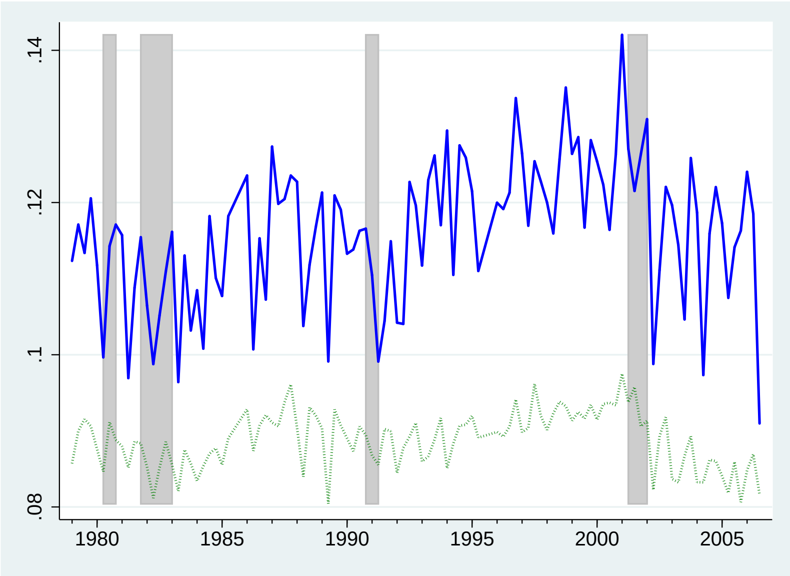


Figure 17: Fraction of hispanics among new hires and all workers.

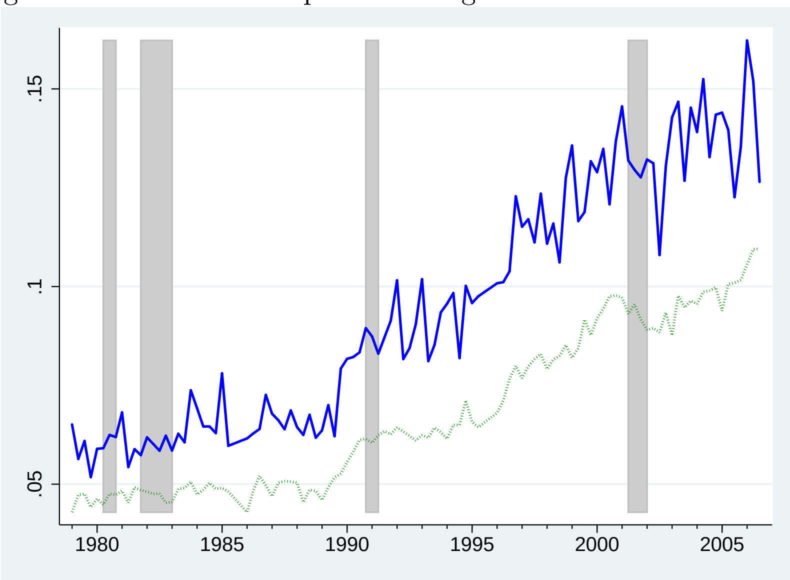


Figure 18: VAR impulse reponses.

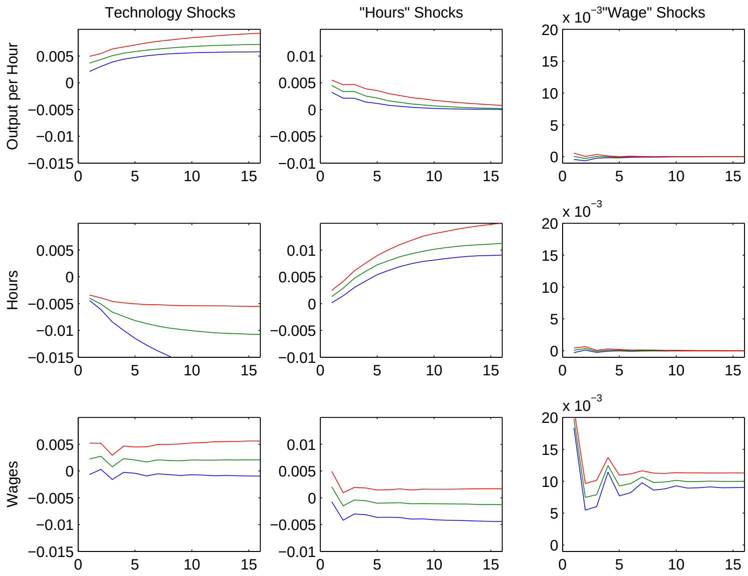


Figure 19: Response of wages of new hires and all workers to technology shocks.