

How Sticky Wages In Existing Jobs Can Affect Hiring*

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Abstract

We consider a matching model of employment with wages that are flexible for new hires, but sticky within matches. We depart from standard treatments of sticky wages by allowing worker effort to respond to the wage being too high or low, rendering the effective wage (wage divided by output) more flexible. Shimer (2004), Pissarides (2009), and others have illustrated that employment in the Mortensen-Pissarides model does not depend on the degree of wage flexibility in existing matches. But this is not true in our model. If wages of matched workers are stuck too high in a recession, then firms will require they provide more effort. In turn, this lowers the value of additional labor, reducing new hiring. We match estimates of wage flexibility by industry from the SIPP to U.S. KLEMS data on wages and productivity for 60 industries for 1987 to 2010. We find that productivity is much more procyclical for industries with more flexible wages, as anticipated by effort choice under sticky wages.

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1. Introduction

There is much evidence that wages are sticky within employment matches. For instance, Barattieri, Basu, and Gottschalk (2010) estimate a quarterly frequency of nominal wage change, based on the Survey of Income and Program Participation (SIPP), of less than 0.2, implying an expected duration for nominal wages greater than a year. On the other hand, wages earned by new hires show considerably greater flexibility. Pissarides (2009, Tables II and III) cites eleven studies that distinguish between wage cyclicality for workers in continuing jobs versus those in new matches, seven based on U.S. data and four on European. All these studies find that wages for workers in new matches are highly procyclical and more cyclical than for those in continuing jobs. This greater wage cyclicality for new hires is typically sizable, especially for the studies on U.S. data.

Reflecting such evidence, we consider a Mortensen-Pissarides matching model of employment with wages that are flexible for new hires, but are sticky–renegotiated infrequently–within matches. But we depart from the sticky-wage literature by allowing that firms and workers must, at least implicitly, bargain over worker effort more frequently than wage rates are altered. Specifically, we treat firms and workers as bargaining each period on the output, and hence effort, expected by the worker. To an extent, this renders wages flexible within matches despite nominal rigidities. Suppose that after a negative shock a worker’s wage, if flexible, would fall by 10 percent. If the wage is stuck in the short run, our model predicts that the firm will require the worker to produce more. In fact, if worker preferences over effort are sufficiently elastic, the worker will be expected to produce at nearly a 10 percent higher effort and output, yielding an effective wage (per unit of labor productivity) that does decline by 10 percent. For salaried workers this extra effort could be viewed as spending more hours at work or taking work home. For hourly-paid workers it could be viewed as increasing the pace of work. In both cases the key is that extra effort and production is not directly accompanied by any wage compensation.

Shimer (2004) and Pissarides (2009), among others, illustrate that the behavior of employment in the Mortensen-Pissarides matching model does not depend on the degree of wage flexibility in existing matches. We show below that this result does not hold in our model with effort choice. Consider a negative shock to aggregate productivity. If existing

jobs exhibit sticky wages, then firms will ask more of these workers. In turn this lowers the marginal value of adding labor, lowering the rate of vacancy creation and new hires. Note this impact on hiring does not reflect the price of new hires, but is instead entirely a general equilibrium phenomenon. By moving the economy along a downward sloping aggregate labor demand schedule, the increased effort of current workers reduces the demand for new hires.

Our model is particularly consistent with events during the great recession. Wage stickiness acts to raise productivity in a recession, relative to a flexible or standard sticky wage model, assuming the sticky wage for current matches is held above its flexible counterpart. Thus it helps to understand why from 2007 to 2009, the brunt of the great recession, the economy exhibited a 10 percent decline in hours work, compared to only a 6 percent decline in real output (from BLS data on multifactor productivity). It is also consistent with an array of anecdotal evidence that firms have required more tasks from their workers since the onset of the recession, rather than expanding their workforces.

We consider two versions of our model. We first allow firms to require different effort levels across workers of all vintages, as dictated by Nash bargaining subject to the sticky wages of past hires. This may require very different effort levels across workers. During a recession the efficient contract for new hires may require low effort at a low wage, while matched workers, whose wages have not adjusted downward, work at an elevated pace. Alternatively, we impose a technological constraint that workers of differing vintages must operate at a similar pace. For instance, it might not be plausible to have an assembly line that operates at different speeds for new versus older hires. We find that the latter model generates considerable wage inertia and greater employment volatility.

Again consider a negative shock to productivity, where the sticky wage prevents wage declines for past hires. The firm has the ability and incentive to require higher effort from its past hires, in lieu of any decline in their sticky wages. But, if new hires must work at that same pace, this implies high effort for new hires as well. For reasonable parameter values we find that firms will choose to distort the contract for new hires, rather than give rents (high wages without high effort) to its current workers. This produces a great deal of aggregate wage stickiness. The sticky wage for past hires drives up their effort and thereby the effort of new hires. But, because high effort is required of new hires, their bargained wage, though flexible, will be higher as well. In subsequent periods this dynamic will continue. High effort

for new hires drives up their wage, driving up their effort in subsequent periods, driving up effort and wages for the next cohort of new hires, and so forth. This model generates a great deal of (counter)cyclical in effort. As a result, it can make vacancies and new hires much more cyclical.

There is only sparse evidence on cyclical of worker effort. Schor (1987) reports on the cyclical of physical activity (effort) for a number of piece-rate workers in manufacturing in the U.K. over years 1970 to 1986. These data show effort to be modestly procyclical. But, for piece rate workers, higher effort does not reduce the effective wage rate. Thus these data do not help us understand how effort of hourly or salaried paid workers will respond under wage stickiness. More relevant to our model is Anger's (2011) study of paid and unpaid overtime hours in Germany for 1984 to 2004. She finds that unpaid overtime (extra) hours are highly countercyclical.¹ Lazear, Shaw, and Stanton (2013) examine data on productivity of individual workers at a large (20,000 workers) services company for the period June 2006 to May 2010, bracketing the great recession. For this company a computer keeps track of the productivity of the workers. They find that an increase in the local unemployment rate of 5 percentage points is associated with an increase in effort of 3.75%.

Our paper proceeds as follows. In Section 2 we present our matching model of employment under sticky wages and endogenous effort. We calibrate a version of the model in section 3. In section 4 we illustrate how our calibrated model responds to aggregate shocks that affect labor demand (e.g., productivity). We show that sticky wages for current matches exacerbates cyclical of hiring when effort responds. In particular, for our benchmark calibration with common effort, the effort response markedly increases the relative cyclical response of unemployment to measured productivity (the basis of the Shimer, 2005, puzzle). It does so by increasing the response of unemployment to productivity, but also by making measured productivity less cyclical than the underlying shock.

Section 5 asks whether our model is consistent with wage productivity patterns across industries, especially the cyclical behavior of productivity in industries with more versus less flexible wages. We measure stickiness of wages by industry based on panels of workers from the Survey of Income and Program Participation for 1990 to 2011. We find that productivity

¹This is in sharp contrast to cyclical in paid overtime hours. Quoting the paper: "Unpaid hours show behavior that is exactly the opposite of the movement of paid overtime."

(TFP) is much more procyclical in industries with more flexible wages; and this impact is more important across industries where labor is more important as a factor of production. These findings align with our model. However, we do not see that wages are more procyclical for industries with flexible wages, suggesting that frequency of wage change may not capture wage flexibility particularly well.

2. Model

Transitions between employment and unemployment are modeled with matching between workers and firms, as in the standard Diamond-Mortensen-Pissarides (DMP) framework, but allowing for an choice of labor effort at work.

2.1. Environment

- **Worker:** There is a continuum of identical workers whose mass is normalized to one. Each worker has preferences defined by:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ c_t + \psi \frac{(1 - e_t)^{1-\gamma} - 1}{1 - \gamma} \right\},$$

where c_t denotes consumption in period t and e_t the effort level at work. The time discount factor is denoted by β . It is assumed that the market equates $(\frac{1}{1+r})$, where r is the rate of return on consumption loans, to this discount factor; so consumers are indifferent to consuming or saving their wage earnings. Each period, an individual worker is either employed or unemployed. When employed (or matched with a firm), a worker is paid with wage w_t and exerts the effort e_t . The parameter γ reflects the worker's willingness to substitute effort levels over time. When unemployed, a worker engages in job search and is entitled to collect unemployment insurance benefits b . Naturally, an unemployed worker's labor effort is assumed to be zero.

- **Firm:** There is a continuum of identical firms. A firm maintains a single job, either filled (or matched with a worker) or vacant. A matched firm produces output according to a constant-returns-to-scale Cobb-Douglas production technology:

$$y_t = z_t e_t^\alpha (k_t e_t)^{1-\alpha},$$

where z_t denotes the aggregate productivity, k_t capital per effort so that $k_t e_t$ is the total amount of capital employed by a matched firm. The capital market is assumed to be perfectly competitive. We treat capital as mobile across firms, with no adjustment costs. At the optimum, given the constant-returns-to-scale production technology, capital-labor ratio k_t is common across all matches and satisfies:

$$r_t + d = (1 - \alpha)z_t k_t^{-\alpha},$$

where d denotes the capital depreciation rate, hence $r_t + d$ is the rental rate of capital. We treat adjustment costs as prohibitive at the aggregate level, with the aggregate capital stock fixed with respect to cyclical fluctuations.

- Staggering Wage Contract:** Wages for a match are determined through the Nash bargaining between the worker and firm at the first period of employment and will be fixed for T periods as long as the match survives the exogenous match separation shocks. At any period, matches can be categorized into T cohorts according to the age of contract (i.e., the number of periods since the wage contract is negotiated). The number of workers whose contract is j period old is denoted by $N_{j,t}$, where $j = 0, 1, 2, \dots, T - 1$. Thus, there is a distribution of matches over the space of T distinct wage contracts. A measure $\mathbf{N}_t = \mu(\mathbf{w}_t)$ captures this distribution of matches, where \mathbf{w}_t denotes a vector of wages (in the order of age) and \mathbf{N}_t a vector of corresponding matches.
- Choice of Labor Effort:** The effort level by a cohort, e_j , is also determined through the Nash bargaining (to maximize the match surplus) between the worker and firm given the contracted wage. We consider two versions of the model: (i) each worker-firm pair chooses effort level individually and (ii) all workers choose a common level of effort level (due to strong complementarity among labors in production).
- Aggregate Output:** Thanks to the constant-returns-to-scale production technology, aggregate output (Y_t) also exhibits a constant returns to scale in aggregate capital, K_t , and labor, L_t , (which is the sum of efforts of all workers):

$$Y_t = \sum_{j=0}^{T-1} N_{j,t} y_{j,t} = z_t \sum_{\tau=0}^{T-1} (N_{j,t} e_{j,t})^\alpha (N_{j,t} k_t e_{j,t})^{1-\alpha} = z_t L_t^\alpha K_t^{1-\alpha} \quad (1)$$

For simplicity, we assume that aggregate capital is fixed in the short run at \bar{K} and owned by workers with equal share.

- **Matching Technology:** Each period new matches are formed through a constant returns to scale aggregate matching technology:

$$M(u_t, v_t) = \chi u_t^{1/2} v_t^{1/2},$$

where u_t denotes the total number of unemployed workers and v_t the total number of vacancies. The elasticities for u_t and v_t are set equal at one half for convenience, though this roughly consistent with empirical estimates (e.g., Rogerson and Shimer, 2010). Thanks to the CRTS property of the matching function, the matching probabilities for an unemployed worker, denoted by p , and for a vacancy, q , can be described as only a function of the labor market tightness θ as follows:

$$p(\theta) = \chi\theta^{1/2}, \quad q(\theta) = \chi\theta^{-1/2}.$$

Finally, we assume that each period existing matches break at the exogenous rate δ and a firm posts vacancies with the unit cost κ to recruit workers.

2.2. Value functions and choices for labor effort and wages

For simplicity, time subscripts are omitted: variables are understood to refer to time period t , unless marked with a prime ($'$) denoting period $t+1$. Let W_j denotes the value of a matched worker whose wage contract is j -period old and U the value of unemployed worker.² For the matches whose contracts are already specified, i.e., for $j = 0, 1, \dots, T-2$:

$$W_j(w_j; z, \mu) = w_j + \psi \frac{(1-e)^{1-\gamma} - 1}{1-\gamma} + \beta \left\{ (1-\delta)E[W_{j+1}(w_j; z', \mu')|z] + \delta E[U(z', \mu')|z] \right\}. \quad (2)$$

subject to

$$z' \sim F(z'|z) = \text{Prob}(z_{t+1} \leq z' | z_t = z) \quad (3)$$

$$\mu' = \mathbf{T}(\mu, z) \quad (4)$$

²In the definition of W_j , we explicitly include w_j in the list of state variables to reflect the sticky wage contract which was determined j periods earlier.

where the transition operator \mathbf{T} is characterized as:

$$\begin{pmatrix} w'_0 \\ w'_1 \\ \vdots \\ w'_{T-1} \end{pmatrix} = \begin{pmatrix} w^*(z', \mu') \\ w_0 \\ \vdots \\ w_{T-2} \end{pmatrix}, \quad (5)$$

$$\begin{pmatrix} N'_0 \\ N'_1 \\ \vdots \\ N'_{T-1} \end{pmatrix} = \begin{pmatrix} (1 - \delta)N_{T-1} + M(u, v) \\ (1 - \delta)N_0 \\ \vdots \\ (1 - \delta)N_{T-2} \end{pmatrix}, \quad (6)$$

where the newly-employed worker's wage in the next period is denoted by $w^*(z', \mu')$.

For the match whose wage will be newly negotiated in the next period, i.e., $j = T - 1$:

$$\begin{aligned} W^{T-1}(w_{T-1}; z, \mu) &= w_{T-1} + \psi \frac{(1 - e)^{1-\gamma} - 1}{1 - \gamma} \\ &\quad + \beta \left\{ (1 - \delta)E[W_0(w^*; z', \mu')|z] + \delta E[U(z', \mu')|z] \right\}. \end{aligned} \quad (7)$$

The value to the unmatched (unemployed) worker is:

$$U(z, \mu) = b + \beta \left\{ p(\theta)E[W_0(w^*; z', \mu')|z] + (1 - p(\theta))E[U(z', \mu')|z] \right\}. \quad (8)$$

Analogously, let J_j for $j = 0, 1, \dots, T - 1$, denotes the value of the job matched with a worker whose wage contract is j -period old. For $j = 0, 1, \dots, T - 2$:

$$J_j(w_j; z, \mu) = \alpha y - w_j + \beta(1 - \delta)E[J_{j+1}(w_j; z', \mu')|z]. \quad (9)$$

subject to (3) and (4).

For the job whose wage will be negotiated in the next period (i.e., $j = T - 1$)

$$J_{T-1}(w_{T-1}; z, \mu) = \alpha y - w_{T-1} + \beta(1 - \delta)E[J_0(w^*; z', \mu')|z], \quad (10)$$

subject to (3) and (4).

Firms post vacancies (v) until the expected value of hiring a worker equals the cost of vacancy (i.e., the value of vacancy $V(z, \mu) = 0$):

$$\kappa = q(\theta)\beta E[J_0(w^*; z', \mu')|z]. \quad (11)$$

The wage for new bargains $w^*(z, \mu)$ is determined through Nash bargaining between a firm and a subset of newly hired workers:

$$w^*(z, \mu) = \operatorname{argmax}_w \left(J_0(w; z, \mu) \right)^{1/2} \left(W_0(w; z, \mu) - U(z, \mu) \right)^{1/2}. \quad (12)$$

We have imposed that the firm's bargaining parameter coincides with the relative importance of vacancies in the matching function; so the Hosios condition will hold. The first order condition for $w^*(z, \mu)$ is

$$J_0(w^*; z, \mu) = \left(W_0(w^*; z, \mu) - U(z, \mu) \right). \quad (13)$$

Given the wage contract w_j which was determined j periods earlier, the effort level for the j^{th} cohort, $e_j(w_j, z, \mu)$, is also assumed to be determined through Nash bargaining between the firm and a subset of the j^{th} cohort workers:

$$e_j^*(w_j, z, \mu) = \operatorname{argmax}_{e_j} \left(J_j(e_j; w_j, z, \mu) \right)^{1/2} \left(W_j(e_j; w_j, z, \mu) - U(z, \mu) \right)^{1/2} \quad (14)$$

for $j = 0, 1, \dots, T - 1$. This yields the following first order condition for $e_j^*(w_j, z, \mu)$:

$$J_j(e_j^*; w_j, z, \mu) \psi(1 - e_j^*)^{-\gamma} = \left(W_j(e_j^*; w_j, z, \mu) - U(z, \mu) \right) \alpha z k^{1-\alpha} \quad (15)$$

for $j = 0, 1, \dots, T - 1$. Notice that under the flexibly-chosen wage, w^* , from (13) this reduces to $\psi(1 - e_j^*)^{-\gamma} = \alpha z k^{1-\alpha}$; so the marginal disutility of effort gets equated to its marginal product. But under sticky wages this efficiency condition is broken. For instance, if the wage is stuck above w^* , then the marginal disutility of effort will exceed its marginal product. This inefficiency reflects that, under the sticky wage, effort choice must serve the dual purposes of maximizing and dividing match surplus.

If we view workers as operating in the same organization, it may be unrealistic to operate at such varying work rules across employees. For instance, consider workers hired at differing dates operating on the same assembling line. It is impractical to have the assembly line speed up and slow down as it passes workers of differing vintages. More generally, it is presumably difficult for any employer engaging workers in team production to assign expectations of effort and performance that differ so dramatically in level and in rates of change across coworkers. For this reason, we also consider (our preferred benchmark) model with bargaining over a common effort level.

When workers must work a common effort level, we assume that the common effort level, $e(z, \mu)$, is still determined through Nash bargaining between the firm and a subset of its workers. But we now assume that these workers are a representative cross section of the firm's workers with respect to vintages. We assume the Nash bargain is over the weighted average of surpluses from these workers. More specifically, the common effort level is determined according to:

$$e^*(z, \mu) = \operatorname{argmax}_e \left(J \right)^{1/2} \left(W - U \right)^{1/2}, \quad (16)$$

where J_N denotes the weighted average of surpluses of jobs, $J = \sum_{j=0}^{T-1} \left(\frac{N_j}{\sum_{j=0}^{T-1} N_j} \right) J_j$, and $W - U$ denotes the weighted average of surpluses of workers, $W - U = \sum_{j=0}^{T-1} \left(\frac{N_j}{\sum_{j=0}^{T-1} N_j} \right) (W_j - U)$.³ This yields the following first order condition for $e^*(z, \mu)$:

$$J(e^*; z, \mu) \psi(1 - e^*)^{-\gamma} = (W(e^*; z, \mu) - U(z, \mu)) \alpha z k^{1-\alpha}. \quad (19)$$

In this case of common effort, the bargaining of wages and effort can be viewed as a two stage Nash bargaining. When a worker is matched with a job, the wage, fixed for the following J periods, is negotiated according to (12). Once they are hired and engage in production, workers negotiate the common effort level according to (16). The wage determined by first-order condition (13) treats the bargaining parties to the wage as sufficiently small that they ignore any impact of their bargained wage on the anticipated effort level, bargained according to (19). That is, the negotiated wage anticipates the future negotiated effort levels, but does not attempt to influence these choices.

³One could view the Nash bargaining over the weighted averages of surpluses as a Nash bargain between a firm operating the aggregate production technology derived above and a representative household (e.g., a family made of workers). For example, when the values of firm and household are defined as follows, respectively,

$$J(e; z, \mu) = z \left(\frac{\bar{K}}{L} \right)^{1-\alpha} e - \bar{w} + \beta(1 - \delta) E[J(e'; z', \mu') | z] \quad (17)$$

and

$$W(e; z, \mu) = \bar{w} - b + \psi \sum_{j=0}^{T-1} \left(\frac{N_j}{\sum_{j=0}^{T-1} N_j} \right) \frac{(1 - e_j)^{1-\gamma} - 1}{1 - \gamma} + \beta(1 - \delta - p(\theta)) E[W(e'; z', \mu') | z]. \quad (18)$$

where \bar{w} is aggregate wage. It is straightforward to show that $J = \sum_{j=0}^{T-1} \left(\frac{N_j}{\sum_{j=0}^{T-1} N_j} \right) J_j$ and $W = \sum_{j=0}^{T-1} \left(\frac{N_j}{\sum_{j=0}^{T-1} N_j} \right) (W_j - U)$.

We considered an alternative multi-party bargaining protocol for the common effort choice, specifically, $e^*(z, \mu)$ chosen according to:

$$e^*(z, \mu) = \operatorname{argmax}_e \Pi \left(J_j(e; z, \mu)^{\frac{1}{2}} (W_j(e; z, \mu) - U(z, \mu))^{1 - \frac{1}{2}} \right)^{\frac{N_j}{N}}. \quad (20)$$

This objective function is the geometric mean of the objective functions in individual Nash bargainings for effort. The resulting first-order condition for effort closely resembles that under our bargaining protocol, except that the arithmetic means for firm and worker surpluses across jobs are replaced by their harmonic means. The two FOCs are only identical if the ratio of the arithmetic mean of surpluses of workers to the arithmetic mean of surpluses of jobs is equal to the ratio of the harmonic mean of surpluses of workers to the harmonic mean of surpluses of jobs. Although these ratios will not be exactly equal in the economy subject to fluctuations, our simulations suggest they do not diverge very far. For our common effort model from (16), simulated to generate time series of length 3,000 periods, the difference between the two ratios clusters closely near zero, with 99.5% of observations less than one-tenth of one percent in absolute size. In order to solve the multi-party bargaining for effort choice, we need to know the fractions of each cohort out of the total employed workers, i.e., $N_{j,t}/N_t$ for $j = 0, 1, \dots, T - 1$ and for all t to compute the harmonic means. This dramatically increases the dimension of the state space, making it impractical to compute the equilibrium. For this reason we only obtain and present results for the bargaining protocol (16).

3. Calibration: Benchmark

Imposed Parameters The period is a quarter. The discount factor, β is set to 0.99, implying an annualized real interest rate of 4%. The real interest rate (1%), combined with the capital depreciation rate, $d = 2.5\%$, yields a steady-state quarterly rental rate of capital (marginal product of capital), $r + d$, is 3.5%.

Key parameters for the impact of current-worker wage stickiness to affect hiring are the duration of wage contracts, the labor share in production, and the Frisch elasticity of labor effort. In our benchmark, the duration of a wage contract is one year (four quarters): $T = 4$; but we also examine the effect of longer contracts. A lower labor share implies a less elastic

aggregate labor demand schedule. In turn, this means higher effort from existing workers in a recession will crowd out more hiring. For our benchmark, labor share parameter in production is $\alpha = 0.64$. This implies a very elastic aggregate labor demand, with elasticity of $\frac{1}{1-\alpha} = 2.78$. We also consider lower values for α .

The Frisch elasticity of labor effort $\frac{1}{\gamma} \frac{1-e}{e}$, reflects both the parameter γ and the level of effort. We first normalize the average effort (by choosing ψ accordingly) to be 1/2 in the steady state. This implies the Frisch elasticity is $\frac{1}{\gamma}$. This is a difficult elasticity to calibrate, given that effort is typically not observed. For our benchmark simulations we set $\gamma = 1$ for a Frisch elasticity for effort of one. If we compare this choice to estimates of the Frisch elasticity for the workweek margin, it is in upper range of estimated values surveyed by Hall (2009). For salaried workers we might anticipate a larger elasticity for effort than the workweek, as effort movements in our model would reflect movements in the weekweek as well as intensity per hour for salaried workers. For hourly paid workers, we might anticipate a smaller elasticity for effort than for the workweek. Schorr (1987) reports a time-series for physical activity of 131,500 piece-rate workers in a standing panel of 171 British factories for years 1970 to 1986. The effort measure represents the ration between actual effort and a standard level of intensity as defined by "time and motion" men. Shor regresses effort on hours per week in British manufacturing as well as additional variables. The estimated elasticity of effort with respect to the workweek varies from 0.52 to 0.60 across five specifications (with standard errors of about 0.14). Bils and Cho (1994) take this as an estimate of the relative Frisch elasticities for the effort versus workweeks margins. This would suggest a smaller Frisch elasticity for effort than for the workweek for hourly paid workers. For this reason, we present results employing a smaller Frisch elasticity for effort of 0.5.

The exogenous aggregate productivity shock follows an AR(1) process in logs:

$$\log z_{t+1} = (1 - \rho_z) \log \bar{z} + \rho_z \log z_t + \epsilon_{t+1}, \quad \epsilon_{t+1} \sim N(0, \sigma_z^2),$$

where $\rho_z = 0.95$ and $\sigma_z = 0.007$, following Kydland-Prescott. The unconditional mean of the aggregate productivity ($\log \bar{z}$) is chosen to normalize the steady state output to one.

Targeted Parameters Other parameters are chosen to match the following targets in the steady state. The labor-market tightness ($\theta = v/u$) is normalized to one. The match

efficiency ($\chi = 0.6$) is chosen so that the job finding rate is $p(\theta) = \chi\theta^\eta$ is 60% in steady state. The job separation rate ($\delta = 4\%$) is chosen so that the unemployment rate is 6.25% in the steady state. The utility parameter for leisure (ψ) is chosen to generate the steady state effort level of 1/2. In steady state wages of all cohorts are the same and equation (12) holds for all $j = 0, 1, \dots, T - 1$ and hence for $j = N$. From equation (16),

$$\psi = \alpha k^{1-\alpha} (1-e)^\gamma = \alpha \left(\frac{1-\alpha}{r} \right)^{\left(\frac{1-\alpha}{\alpha} \right)} (1-e)^\gamma$$

The vacancy posting cost (κ) is chosen to satisfy the free entry condition in (11). Given the steady-state wage $w_{ss} = 0.6787$, the unemployment benefit (b) is chosen to match the replacement rate (in terms of utility) $b / \left(w_{ss} + \psi \frac{(1-e)^{1-\gamma}-1}{1-\gamma} \right)$ is 75%.

4. Results

We illustrate how our model responds to an aggregate shock that affects labor demand using a negative productivity shock. In particular, we show that sticky wages for current matches can exacerbate cyclicalities of vacancy creation and hiring when effort can vary.

4.1. Impact of Sticky Wages with Fixed Effort

First, however, consider the impact of wage stickiness under fixed effort. Figure 1 shows the response of the model (with both flexible and sticky wages) to a persistent decrease in aggregate productivity, a one percent decrease with autocorrelation of 0.95 (shown in the first panel). The second panel shows the responses of nominal wages, first for new matches or those re-bargaining, then for all workers. Wages of new bargains respond similarly for both the flexible (denoted by “--”) and sticky wage (denoted by “-”) models, as wages are flexible for new hires even under the sticky-wage scenario. The new hire wage responds slightly less under sticky wages, however, reflecting that the new hire wage will be stuck slightly lower for the next three quarters than its expected value under fully flexible wages. But the expected present value of wages for new hires is the same under flexible and sticky wages. The aggregate wage responds much less on impact under sticky wages since only those one-fourth of workers whose wage contract expired, plus new hires, show any wage response. After four quarters all wages will reflect wages bargained after the shock to productivity. So we see the aggregate wage coincides under flexible or sticky wages at that point.

The bottom panels of Figure 1 illustrate the responses of output, measured TFP, employment, and labor market tightness (vacancies relative to unemployment) to the productivity shock. As anticipated by the literature, these responses are identical under flexible and sticky wages—wage stickiness has no impact on the real economy. Note also that the model generates little persistence in output beyond that directly built into the productivity shock process.

4.2. Introducing Bargaining over Worker Output (Effort)

Figure 2 presents impulse responses allowing for bargaining over effort. We consider three scenarios: (1) fully flexible wages, (2) sticky wages for four quarters, with effort a separate choice variable across worker vintages, (3) sticky wages for four quarters, with a common effort choice across workers. The panels in Figure 2 illustrate the responses of key variables, such as wage rates and effort, to a one percent decrease in productivity (again with autocorrelation of 0.95) under each of the three scenarios.

Focus first on the case of completely flexible wage rates (denoted by “-.-”). The top three panels depict the impulse responses in the newly-bargained wage, the average wage, and average effort. Under flexible wages, of course, wages of new bargains and the average wage decrease by the same amount. The decrease in wage reflects both the negative shock to productivity as well as the negative effort response. For the assumed Frisch elasticity of one, the effort response is nearly one-for-one to the productivity shock. Because the wage reflects effort as well as exogenous productivity, the wage decreases nearly twice as much as the underlying shock. Output, measured TFP, and the rental rate on capital (panels 4-6) all show decreases of the same magnitude as in the flexible wage, as each also responds to effort as well as the productivity shock. The next two panels (7 and 8) in Figure 2 give the responses in employment and labor market tightness. Employment responds with a lag, bottoming in the third period. This reflects not only the search friction, but also the short-run decrease in the rental rate of capital driven by the decrease in worker effort. Thus the cyclical nature of the intensive effort margin acts to reduce the response in employment.

Next consider sticky wages with effort a separate choice across worker vintages (denoted by dashed line “--”). The first two panels of Figure 2 show that, while the average wage responds initially only about one-third as much as under flexible wages, the new-hire wage

actually responds more for new bargains when wages are sticky for past bargains. The reason for this is apparent from the final panel in Figure 2, depicting the response in effort across worker cohorts. The initial response for workers under sticky wages (i.e., old contracts) is an effort increase of 0.8 percent. But that effort increase keeps the marginal product of labor lower (along the downward-sloping marginal product of labor schedule) than it would be under flexible wages. For this reason, workers under new bargains decrease effort more under sticky wages and, as a result, the wage decreases more for new bargains.

Overall, however, as depicted in the third panel, average effort increases reflecting a sharp increase in effort for the workers employed under sticky wages. As a result, the decrease in output and measured TFP (panels 4 and 5) are each 40 percent less than under flexible wages. This increase in effort, while reducing the impact on output, magnifies the initial impact on employment. By increasing effort, the sticky wage increases effective labor relative to capital. Thus, viewed from the aggregate economy it drives the marginal product of new hires lower than it would be otherwise. From the perspective of an individual firm this is manifested in a smaller decrease in the rental rate of capital than under flexible wages. As a result, both employment and labor market tightness drop slightly more initially under sticky wages (panels 7 and 8), though admittedly this effect is small and short lived.

After three quarters the relative impacts on average effort under flexible versus sticky wages actually reverse, with average effort, output, and measured TFP all lower under sticky than flexible wages. The reasoning is as follows. On impact the negative shock induces a sharp rise in effort for workers who are under sticky wages. But this effect is gone by the fourth period, when all wages have been renegotiated. At the same time, effort and wages are particularly reduced for the bargains that occur during the first few periods after the shock. But because these wage rates are locked in for four periods, it will also lock in reduced effort levels for these workers for four periods. The total impact is a humped shaped response in average effort, output, and measured TFP, despite the assumption of no such shape for the underlying productivity shock.

Returning to the final panel of Figure 2, we see that the model yields dramatically different responses in effort levels across the cohorts of workers. While the workers under sticky bargains increase effort by nearly enough to keep their productivity constant, the newly hired and newly negotiating workers adjust their effort by an even greater magnitude, but in the

opposite direction. If we view these workers as operating in the same organization, then it may be unrealistic to operate at such varying work rules across employees. For instance, consider workers hired at differing dates operating on the same assembling line. More generally, it is presumably difficult for any employer engaging workers in team production to assign expectations of effort and performance that differ so dramatically in level and in rates of change across coworkers. For this reason, we now move to our preferred (benchmark) model with bargaining over a common effort level (denoted by solid line “—”).

Looking at the first panel of Figure 2, under common effort we see that, even though the wage in new bargains is flexible, it decreases much less than the magnitude of the productivity shock; it does decrease by nearly as much as measured TFP. As a result, there is a good deal of inertia in the average wage. It decreases very little for the first few quarters. It only coincides with its fully flexible wage counterpart after sixteen quarters—twelve quarters after all wages have been bargained anew. Thus the model provides considerable wage inertia.

The intuition is as follows. In bargaining over effort, firms face a tradeoff between what is efficient for new wage bargains and what is most profitable for workers under sticky wages. After a negative shock the efficient new-wage bargain asks for lower effort, combined with deeper wage cuts. But, because workers with dated wage bargains are overly paid, the firm is essentially throwing away profits if it foregoes asking more from these workers. The optimal bargain over effort trades off these objectives—asking somewhat less than it could of sticky wage workers and settling for a less than efficient bargaining for new wages, by asking for more effort and paying higher wages. For our benchmark calibration, the effort choice is dominated by the desire to obtain the possible effort level from the sticky-wage workers. We see this from observing that average effort changes to nearly offset the shock to productivity.

Why does the wage inertia persist well after all wages are renegotiated? Consider new hires in the first period after the shock. Because effort is increased for these workers, their wage is higher than it would be otherwise. But then, over the next three quarters, the wage for these workers is stuck higher, acting to generate a higher effort choice over those three quarters. In turn, this acts to push all new bargains over those three quarters to adopt higher effort and higher wages. But, in turn, those subsequent bargains will push up effort and wages for workers hired in still later periods. Thus the wage rigidity pushes up subsequent effort, which pushes up subsequent wages, pushing up subsequent effort, and so

forth.

This strong countercyclical effort response considerably mutes the cyclicity of the rental rate of capital (panel 6). In turn, this exacerbates the cyclicity of vacancy creation and employment. Looking at the response of employment, we see that employment responds by 60 percent more to the shock in the first year relative to the model with flexible wages. Thus the existence of sticky wages for workers in older contracts magnifies cyclicity of new hires, even though wages are flexible for these workers. In fact it is worth stressing that wage rates do respond considerably more for new hires, than for existing workers, but by less than the negative shock to productivity.

4.3. Robustness to parameters

Here we explore robustness of our results to a few key parameters, the duration of the nominal wage stickiness, the Frisch elasticity of substitution that dictates the willingness of workers to vary their effort, and the short-run elasticity of the aggregate labor demand schedule.

Our benchmark calibration assumes wages are sticky in matches for four quarters. Several studies of payrolls at large firms (Wilson, 1999, Altonji and Devereux, 1998, LeBow, Sachs, and Wilson, 1999) find some set of workers, perhaps 20 percent, show no wage change even over a year. More recently, employing SIPP data, Barrattieri, Basu, and Gottschalk (2010) estimate a duration of wages of 6 quarters, or perhaps much more depending on sample and other choices. Our analysis of the SIPP below suggests nominal wage durations on the order of five or six quarters. Here we illustrate the role of the assumed wage stickiness by extending the duration of wage contracts, generously, to 8 quarters. Figure 3 presents the impulse response of three models (flexible wages and sticky wage with individual and common effort choice) with a 8-quarter wage contract. The mechanism we discussed with 4-quarter contracts is considerably strengthened. Compared to 4-quarter contracts, the average wage is more sluggish, causing effort to remain elevated longer. For example, average effort now remains 0.8% higher than the steady state after four quarters, compared to 0.4% in Figure 2. As a result, the newly bargained wage drops very little. The impact of the wage rigidity on employment is larger—the drop in employment is nearly twice as large under sticky wages with common effort as under flexible wages.

In Figure 4 we present results decreasing the Frisch elasticity from 1 to 0.5 ($\gamma = 2.0$).

Wage durations are again four quarters. The willingness of workers to vary effort level is directly related to this elasticity. Therefore, by cutting the Frisch elasticity to one-half, our results move qualitatively toward a sticky-wage model with fixed effort. Because it is more costly to ask for higher effort from workers under on-going sticky wage contracts, their effort increases less. As a result, the wages of newly bargained workers fall more in response to a negative productivity shock. The impact of wage stickiness on employment is lessened modestly compared to the case of Frisch elasticity equal to one.

The impact of sticky wages for existing workers on the cyclicalities of hiring of new workers is directly linked to the short-run elasticity of the aggregate labor demand schedule. From an aggregate perspective, increased effort by existing workers, by reducing labor's marginal product, discourages hiring. The impact of this effect is thus greater if the marginal product of labor schedule is steeper. For our model, with Cobb-Douglas production, the elasticity of marginal product of labor with respect to labor input is minus capital share. For our benchmark calibration this equals -0.36. In turn, this implies a very elastic labor demand curve, with elasticity of labor demand with respect to the wage, holding all else constant, of -2.78. In Figure 5 we illustrate results doubling the capital share, so that the elasticity falls to -1.39. For our preferred model with common effort, wage stickiness now more than doubles the impact of the shock on employment; this impact of stickiness is 50 percent larger than our benchmark calibration with very elastic labor demand.

4.4. Comparison to the U.S. Data

Can our model account for the observed movement of unemployment over the business cycle? To answer this, we feed in a series of productivity shocks that resembles the cyclical components of multifactor TFP from the BLS. The upper panel of Figure 6 shows the benchmark (common effort with sticky wages) model's unemployment rate and measured TFP when we feed in the (H-P filtered) BLS-measured TFP (for 1987: 1Q - 2012: 4Q) as productivity shocks. For comparison, we also plot the actual time series of BLS-TFP and unemployment rate (in dotted lines). The unemployment rate from the model underpredicts that in the data. According to our model, however, effort moves counter-cyclically in response to exogenous productivity shocks. As Figure 6 shows, the measured TFP in our model moves much less than that in the data. In order to obtain the similar degree of

volatility of measured TFP between the model and data, the model requires a bigger shock.

When we multiply the (cyclical components of) BLS-TFP by 1.8 (keeping its autocorrelation constant), the volatility of the model-generated TFP matches that in the data. Under this adjusted productivity shocks, the model now generates a much larger responses in unemployment rates. For example, in terms of standard deviation, the model now accounts for about three-fourths of volatility (0.58% in the model vs. 0.75% in the data). Thus our model has a fairly small Shimer (2005) puzzle, despite the replacement flow value of unemployment being calibrated to only 75 percent. There are two reasons for this: (1) The effort response in the model exacerbates the response of unemployment to the productivity shock, as outlined above. (2) The countercyclical effort response masks much of the cyclicity of the underlying shock, so that unemployment fluctuations look larger relative to those in productivity.

We repeat the same experiment with the Frisch elasticity of 0.5 ($\gamma = 2$) in Figure 7. As the effort becomes less responsive, the model generates a smaller response in unemployment. This, at the same time, implies a lesser counter-cyclical effort. To match the volatility of TFP in the data, it requires us to multiply the productivity shock (based on BLS-TFP) by 1.42. Under this scenario, the model accounts for one-thirds of unemployment volatility in the data as the model's standard deviation becomes 0.24. So much of the Shimer puzzle reemerges.

5. Empirical Results

The model provides a channel for wage stickiness to affect productivity (TFP), and through that channel to inversely affect the number of workers hired. From data on the aggregate economy it is difficult to decipher the predictions of our model from reasonable alternatives without knowledge of the underlying shocks to the economy. For instance, our model predicts that productivity is less procyclical than under flexible wages. But without knowing the true underlying shocks to productivity, as well as their correlation with other shocks, it is hard to evaluate the model based on the cyclicity of productivity. Measured TFP clearly does not provide a measure of productivity shocks in a setting, such as ours, with variations in unmeasured inputs.

As an alternative, we examine cross-sectional patterns in wages and productivity. More exactly, we examine TFP behavior in 60 industries for 1987 to 2010 drawn from the BLS Multifactor Productivity measurement program (U.S. KLEMS). The first two subsections describe the KLEMS data then show that there is a strong correlation between relative industry wage movements and relative industry TFP movements that is only present to the extent labor is important as a factor of production. The third subsection employs data from the Survey of Income and Program Participation (SIPP) for 1996 to 2011 to measure wage stickiness across our 60 sectors. We then examine how wages and TFP responds cyclically for industries with more versus less sticky wages.

5.1. Cross-Industry Data

The U.S. KLEMS data (<http://www.bls.gov/mfp/>) provide nominal and real values for gross output, inputs of intermediates, labor, and capital annually from 1987 to 2010 for 18 manufacturing and 42 non-manufacturing sectors. These industries are listed in Table 2, together with their relative values added. The KLEMS data exclude the government, nonprofit, and private household sectors, as production for these sectors is measured by inputs; so productivity is not measured. As a result, the shares of some sectors here, most notably Education Services, are reduced compared to national income accounts.

The KLEMS data provide information on industry productivity, as measured by real gross output relative to real inputs (gross output TFP). We also construct measures of value added TFP measured by real value added relative to inputs of capital and labor. Industry real value added and its deflator are constructed using the Divisia method from values and prices for gross output and intermediate inputs, as described by Basu and Fernald (1997). (In this construction we equate intermediate inputs cost shares with their revenue shares; so, implicitly we assume a zero rate of profit.)

We adjust the KLEMS TFP measure for the impact of procyclical utilization of capital. We adjust both the TFP and wage rate measures from the KLEMS for cyclical variations in the composition of the workforce. To adjust for capital utilization we follow Bils, Klenow, and Malin's (2012)–BKM for short–who employ data on utilization rates of capital constructed by Gorodnichenko and Shapiro (2011) for two-digit manufacturing for 1974 to 2004. BKM find that a one-percent increase in the labor to capital stock ratio is associated with a one-third

percent increase in the utilization rate of capital. So we adjust TFP by subtracting capital share in producing multiplied by one-third times movements in the labor-capital ratio. We adjust both the industry wage and industry TFP for worker composition as follows. Using the SIPP data panels for 1990 onward, we estimate the ratio of new-hire wages to the average industry wage for each of the 60 industries. This ratio averages 0.85 across the industries, varying from 0.67 in water transportation to 0.97 for computing services. We assume that industry fluctuations in employment, relative to its HP trend, add or subtract workers that differ from industry average wage and productivity according to these ratios. We adjust industry wages to undo this composition impact by adding back to the industry wage the percent difference between the average and new-hire wage multiplied times the industry employment fluctuation. Similar, we adjust industry TFP by adding this same amount to fluctuations in TFP, multiplied by labor’s share in production.⁴

These adjustments actually have little impact on the results below. Taken together, the adjustments for capital utilization and worker composition make TFP on average slightly less procyclical and wage rates modestly more procyclical. But the adjustments scarcely affect the primary coefficients of interest, that is, how industry wage flexibility affects cyclicity of TFP, inputs, and wages.

5.2. Cross-Industry Wage and Productivity Patterns

Our focus is on higher frequency, cyclical movements in wages and productivity. For this reason, we remove an HP-filter for each series, with the HP-filter defined separately for each industry, using the smoothing parameter of 6.25 suggested by Ravn and Uhlig (2001) for annual data. The first column of Table 3 reports the result of projecting an industry’s TFP fluctuations on its fluctuations in wage rate. The regression includes a full set of year dummies; so all fluctuation reflect relative movements across industries. The regression shows that the relative fluctuations in wages and TFP are extremely correlated, with a one-percent wage movement associated with a 0.54 percent movement in value-added TFP in the same direction.

⁴We do not have employment series, only total hours, for 9 of the 60 KLEMS. For these industries we assume that 76% percent of industry hours fluctuations occur through the employment margin, where this 76% is estimated from regressing employment fluctuations on total hours fluctuations for those industries with both series.

Of course, a positive correlation between fluctuations in relative wage and TFP does not establish that causality runs from wage to TFP, as suggested by our model. If industry labor supply is highly industry-specific, then we might expect an increase in TFP to drive up industry wage, even if TFP is not affected by the wage. For this reason, we focus for much of the balance of the paper in stratifying industries by wage stickiness. But there are several features of the industry data that suggest that relative TFP movements do not drive relative wages.

For one, the relationship between industry wage and TFP only applies at cyclical frequency. If we repeat the regression from Table 3, column 1, but instead relate the relative industry HP trends to TFP to industry trends in wage there is no relationship. (The coefficient actually becomes slightly negative, at -0.02, with standard error 0.01.)

Second, the strong positive relationship between industry wage and TFP only holds to the extent that labor is important for production in an industry. This is shown by the regression in Column 2 of Table 3, which adds an interaction of an industry wage movement with the industry's labor share in value added. (Labor share is measured by the industry's HP trend in labor share.) The regression implies that for an industry with hypothetically 100 percent labor share, TFP moves one for one with the wage movement (actual estimate 1.13 percent, with standard error 0.15 percent); but as labor share goes to zero the impact of wage on TFP is zero. Our model, with wage rates driving effort and TFP, clearly implies that the impact of wage on TFP is proportional to labor's share in production. The reverse channel, high TFP driving up the wage, does not explain why the relation only holds proportionate to labor's importance in producing. The last two columns of Table 3 repeat the exercise, but for TFP for gross output. Again we see fluctuations in the real wage, weighted by labor's share in producing gross output, are associated with fluctuations in TFP of the same magnitude.

A more direct problem for the channel from TFP to wages is that it is not apparent that the industry movements in TFP generate movements in labor demand. When we regress industry hours on industry TFP, we find that a one percent increase in TFP is actually associated with a small decrease in hours of 0.05 percent (with standard error of 0.01 percent). So industry fluctuations in TFP, since they are not associated with an increase in labor, should not act as a strong force to increase the industry relative wage.

5.3. SIPP Data for Measuring Wage Flexibility

We construct measures of wage flexibility—frequency of wage change—for all workers as well as for each of our 60 industries. We can then ask whether TFP responds differently cyclically for industries with more versus less flexible wages.

Our estimates of wage flexibility are based on multiple panels of the Survey of Income and Program Participation (SIPP) representing most of the period since 1990. The SIPP is a longitudinal survey of households designed to be representative of the U.S. population. It consists of a series of overlapping longitudinal panels. Each panel is three or more years in duration. Each is large, containing samples of about 20,000 households. Households are interviewed every four months. At each interview, information on work experience (employers, hours, earnings) are collected. Each year from 1984 through 1993 a new panel was begun. New, somewhat longer, panels were initiated in 1996, 2001, 2004, and 2008. In our analysis we employ the 8 panels from 1990 onward. (The 1984-1989 panels contain less reliable information on employer changes.) The SIPP interviews provide employment status and weeks worked for each of the prior four months. But earnings information is only collected for the interview month; so we restrict attention to the survey month observations.

For our purposes the SIPP has some distinct advantages. Compared to a matched CPS sample, we are able to calculate workers' wage changes across multiple surveys and at intervals of four months, rather than 12. It also provides better information for defining employer turnover. The SIPP has both a larger and more representative sample than the PSID or NLS panels and, most importantly, individuals are interviewed every four months. Barattieri, Basu, and Gottschalk (2010)'s—BBG henceforth—employ the 1996 panel of the SIPP in their recent paper measuring frequency of wage change. (They cite these same advantages in choosing the SIPP data.) We compare our results to BBG's below.

We restrict our sample to persons of ages 20 to 60. Individuals must not be in the armed forces, not disabled, and not be attending school full-time. We only consider wage rates for workers who usually work more than 10 hours per week and report monthly earnings of at least \$100 and no more than \$25,000 in December 2004 CPI dollars. Any reported hourly wage rates that are top-coded or below \$4 in December 2004 dollars are set equal to missing. Although the SIPP panels draw representative samples, in constructing all

reported statistics we employ SIPP sampling weights that account for sample attrition. We also weight individuals by their relative earnings in the sample period, as this is consistent with the influence of workers for aggregate labor statistics.

We calculate frequency of wage changes over the four month interval between interviews for workers who remain with the same employer for their main job. For the 1990 to 1993 panels we define workers as stayers if the SIPP employer ID remains the same across the surveys. We employ the 1990-1993 SIPP revised employer ID's, which have been edited at the Census to be consistent with information available in the non-public Census version of the data. Such edits have not been undertaken for 1996 and later panels. For the later panels we see a number of changes in employer ID that appear (based on wages, et cetera) to not represent an employer change. For the later panels we define stayers based on responses to when the reference job began. More exactly, we define the worker as a new hire (not stayer) if at the current survey they report that the job began within the last four month, or if in the prior survey they report that the reference job had ended by the survey. (This latter case is relatively rare.) We additionally call the worker a new hire if the employer ID and the industry of employment both changed across interviews. We similarly calculate frequency of wage changes across eight-month intervals for those workers we classify as stayers over that 8-month interval.

There are multiple potential measures of wages in the SIPP. Employed respondents report monthly earnings. In addition, a little over half of those working report an hourly rate of pay. For each worker we also calculate a weekly wage by dividing monthly earnings by the number of weeks worked in the month. We define a worker's wage as not changing if any of these three measures remains the same across the surveys.

We first report rates of wage change for all workers, then separately for our 60 KLEMS industries. The SIPP provides a 3-digit industry code for employer, allowing us to make the mapping of SIPP workers to KLEMS industries. For a few of the smaller KLEMS industries there are so few SIPP workers that the SIPP rates for that industry would be unreliable. In these few cases we use the rates for what we view as a similar industry. (For instance we use rates for Construction for the Pipeline Transportation industry, and rates for Miscellaneous Professional, Scientific, and Technical Services for the Management of Enterprises industry. The total sample, combining observations from the 1990 to 2008 panels is large. For instance,

for calculating 4-month frequency of wage changes for stayers it equals 780,328 persons; of these, 653,615 are mapped to one of our 60 KLEMS industries.

5.4. Measuring Wage Flexibility

A concern with using micro data on wage changes is that measurement errors will contribute to the reported frequency and volatility of wage changes. BBG (2010), for instance, deal with measurement error by keeping only those wage changes that can be viewed as a time-series structural shift for the individual's wage series. This removes relatively brief wage episodes or those that are followed by a subsequent change in the opposite direction. BBG report that the procedure removes 63% of wage changes for hourly-paid workers. We estimate that their procedure for salaried workers removes about 90% of reported wage changes. (BBG put primary emphasis on hourly workers.)

We also allow for measurement error in the individual wages. But we adopt a simpler and, at least ex post, more conservative representation for the measurement error. We make the following assumptions regarding measurement error in the pay variables. (i) The probability of measurement error is the same for all individuals within an industry within a particular panel of the SIPP. This implies the probability is independent of the occurrence of a true wage change or a prior measurement error. (ii) There is zero probability of a true wage change that is followed an exactly opposite true wage change four months later, that leaves the wage exactly unchanged after two subsequent changes. (iii) There is zero probability that the change in measurement error across the wage change will exactly offset the true wage change. Suppose we observe a change in wage that is exactly offset at the subsequent interview. The latter two assumptions lead us to infer that there were no true wage changes.

We consider two models of the frequency of true wage changes: a Calvo assumption of constant probability each four-month period of a wage change, and a Taylor assumption that the nominal wage is fixed for a certain number of periods. We detail the procedure here under the Calvo assumption. Implications under the Taylor assumption follow intuitively from this case. Let α_c be the Calvo probability of wage change over a 4-month period and ϕ be the probability of measuring the wage with error at any interview. Then the probabilities of observing a wage change over a 4-month or 8-month period, Δ_1 and Δ_2 , are respectively:

- $\Delta_1 = \alpha + (1 - \alpha_c)(2\phi - \phi^2)$
- $\Delta_2 = (2\alpha_C - \alpha_C^2) + (1 - 2\alpha_C - \alpha_C^2) * (2\phi - \phi^2)$

We express Δ_1 and Δ_2 here as the probability of a true wage change plus one minus that probability times the probability measurement error driving a wage change. For 4 or 8-month intervals, the probability of measurement error driving a wage change is $(2\phi - \phi^2)$. But across 4 and 8 months the probabilities of a true change are α_C versus $(2\alpha_C - \alpha_C^2)$. Given measures for Δ_1 and Δ_2 , we can calculate the two parameters α_C and ϕ . With:

$$\alpha_C = \frac{\Delta_2 - \Delta_1}{1 - \Delta_1}. \quad (21)$$

And ϕ solves the quadratic equation:

$$0 = \phi^2 - 2\phi + \frac{2\Delta_1 - \Delta_1^2 - \Delta_2}{1 - \Delta_1}. \quad (22)$$

If, instead, we adopt the Taylor assumption then equations (21) and (22) remain intact, except the probability of a change over two periods simply equals $2\alpha_T$, where α_T is the 4-month Taylor probability of a true wage change. (This assumes $\alpha_T < 1/2$, which holds for our estimates.) The implied relation between the Taylor calculated frequency and the Calvo calculated frequency is $\alpha_T = \alpha_C / (1 + \alpha_C)$.

Table 4 presents the frequencies of wage changes, over 4 and 8 months, the implied Calvo and Taylor true 4-month frequencies, and the likelihood of measurement error under the Calvo assumption. As discussed above, we weight observations in the SIPP by the worker's monthly earnings, as well as a SIPP sampling weight. In calculating the Calvo and Taylor parameters we use 4-month frequencies calculated just for 8-month stayers so that the 4 and 8-month changes are calculated for the same sample. These 4-month frequencies differ only slightly from those reported in the first column of Table 4. We present results separately for the 1990-1993, 1996, 2001, 2004, and 2008 SIPP panels. When we aggregate, we give the combined 1990-1993 panels 1.5 times as much weight as the others, as those panels combined span about 6 years, while the others span about 4 years.

We focus initially on the first line, results for the 1990-93 panels, in order to illustrate the approach. These panels show very high rates of wage changes, 68% over 4 months and 76% over eight. But, in the absence of substantial measurement error, the data are not

consistent with either the Calvo or Taylor assumptions. For instance, under Calvo, a true 68% frequency over 4 months would imply we should see a 90% frequency over 8 months, rather than 76%. Our approach rationalizes the observed rates under Calvo if the true 4-month frequency is 0.26 and the probability of measurement error in wage at each survey equals 0.34. Under the Taylor assumption, because it exhibits an increasing hazard of wage change, the relative frequencies at 4 and 8 months would imply even greater measurement error and a smaller 4-month true frequency of 0.20.

There are considerable differences in the observed frequencies of wage changes across the alternative SIPP panels. The 1996 and 2001 panels show even higher frequencies than do 1990 to 1993. Our estimates interpret this as reflecting slightly higher measurement error for these panels and somewhat more flexible wage rates. The Calvo parameters are calculated at 0.39 and 0.34 for the 1996 and 2001 panels. The last two panels, 2001 and 2004, show much lower rates of wage changes. This is particularly true for the 2008 panel. Our calculations explain the drop in frequencies primarily by a fall in the measurement error rate, from 0.38 in the 2001 panel down to 0.05 by the 2008. For the 2004 panel the implied Calvo and Taylor parameters, 0.28 and 0.22, are actually slightly higher than for the 1990-93 panels; but for 2008 they are substantially lower at 0.19 and 0.16.

The bottom line of the table aggregates the panels. The calculated Calvo and Taylor parameters are 0.29 versus 0.22. If we invert these 4-month frequencies and multiply by the period's length (4-month) we get implied durations of wages of 14 months under Calvo and 18 months under Taylor. Papers in the literature that calibrate wage stickiness typically choose a value of 12 months; so these values are modestly above those. Table 4 also gives the new-hire rate. This rate averages 7.5 weighting by earnings, 9.6 not weighting by earnings. If we treat the new hire wage as flexible, and assume turnover is orthogonal to realization of a wage change, that results in an overall new-wage rate of 0.34 under Calvo and 0.28 under Taylor. If we invert these rates and multiply by 4 months, we get implied durations of 12 months under Calvo and 14 months under Taylor. So these are actually quite close to the typical choice for calibrating of 12 months.

The results in Table 4 combine hourly-paid and salaried workers. But we find very similar frequencies across the groups—a Calvo parameter of 0.30 for hourly versus 0.28 for salaried. The observed frequency of wage change is higher for salaried workers, but our approach

interprets this as primarily reflecting twice as common of measurement errors for salaried workers as for hourly-paid workers.

BBG's (2010) approach yields considerably stickier wage rates. This is despite the fact that their work is based on the 1996 SIPP panel, which shows relatively high rates of wage change. Our estimated rates for the 1996 panel are 40 to 50 percent higher than BGG's preferred estimate for hourly workers and close to ten times as high as their preferred estimate for salaried workers.

Table 2, which list each KLEMS industry, reports the frequency of wage change and rate of measurement error by industry. For convenience it just reports the Calvo case. The Calvo rate varies from lows of 0.22 or 0.23, implying durations of 18 months, for mining industries and passenger transit to highs of 0.33, implying durations of 12 months, for petroleum and coal products, furniture, and other transportation (sightseeing and couriers). The frequency of wage change is not particularly correlated with the other industry characteristics we observe. For instance, its correlations with the durability of the industry good (measured as described in BKM, 2012) and industry labor share are both about 0.1, and not significantly different from zero. For 41 of the 60 industries we have estimates of the frequency of price change from BKM. The correlation of wage flexibility with price flexibility is essentially zero, at 0.05.

5.5. Industry Wage Flexibility and Cyclicalities of TFP

We ask how an industry's cyclical behavior depends on its wage flexibility. We measure the cycle by the behavior of HP-filtered annual U.S. GDP. We regress fluctuations in the industry inputs (real value added minus TFP), TFP, and relative wage on the aggregate cycle (GDP) and the aggregate cycle interacted with stickiness of the wage. Industry TFP is corrected for fluctuations in capital utilization. The relative wage equals the industry wage minus the average wage across all 60 industries. The measure of stickiness is the expected duration of wage in months, calculated under the Calvo assumption. In the interaction we subtract the average expected durations across all industries (14.4 months) so that the coefficient on GDP can be interpreted as holding for an industry with wage duration equal to that mean value. The regressions weight each observation by the industry's relative value added in that year.

The top panel of Table 5 gives results for all 60 industries. The coefficients for GDP imply that, evaluated at mean stickiness, inputs for our 60 industries increase 1.2 percent for a one percent expansion in GDP. TFP and the real wage are both only slightly procyclical. The interaction of GDP with wage stickiness shows that industries with stickier wages display more cyclical inputs and less cyclical TFP. The standard deviation of wage duration equals 1.1 months; so the estimates imply that a one standard deviation increase in wage duration would increase the response in inputs by about 0.2 percent and decrease the response in TFP by about a third of a percent for a one percent increase in GDP. These results qualitatively align with the predictions of the sticky-wage model with bargaining over effort. But we do not see less cyclical wages for the stickier wage windows. In fact the sticky wage measure is associated with more cyclical wages; a one standard deviation increase in stickiness implies a 0.25 percent bigger wage response for a one percent increase in GDP. So this makes the data harder to interpret in light of the model. (We alternatively estimated using a full set of year dummies, rather than just the regressor GDP; but the results for the stickiness interactions were unaffected.)

The next two panels break the sample by labor's share in value added. We split industries by above and below a labor share of 71 percent, as this puts 30 industries into each group. This break is above the mean labor share in our KLEMS data, weighting by industry value added, of 67.2 percent. We find that the impact of wage stickiness on countercyclical TFP is much more significant for the industries with higher labor share. This is consistent with a channel from labor effort to TFP, as that channel should weight by labor's importance. The coefficient for the high labor share industries -0.45 (s.e. 0.14) is a little more than double that for the low labor supply industries. This aligns with the fact that labor share is about twice as high in the high-share industries (81 percent) as in low-share industries (44 percent).

Real output, and therefore TFP, are arguably better measured for goods industries than services, as it is particularly difficult to measure output quality for services. For this reason, in Table 6 we restrict attention to the 24 industries that produce goods (agriculture, mining, construction, and manufacturing industries). Looking at the top panel, we see that the impact of wage stickiness on cyclicalities of TFP and inputs is much stronger for these industries. A one standard deviation increase in wage duration would increase the response in inputs by about one-third of a percent and decrease the response in TFP by more than

two-thirds of a percent for a one percent increase in GDP. The middle two panels break the sample by labor's share in value added; splitting these industries at a labor share of 67 percent puts 12 industries into each panel. We again find that the impact of wage stickiness on countercyclical TFP is driven in proportion to an industry's labor share. The coefficient for high labor share industries -1.13 (s.e. 0.16) is more than two times that for those with lower labor input, -0.47 (s.e. 0.20).

The bottom panel of Table 6 restricts the sample to 14 industries that produce durable goods. We anticipate much more procyclical labor demand for these industries, given the cyclical shift in expenditures toward these goods. When we restrict to durables, we see a large impact of wage stickiness on cyclical TFP. The estimates imply that a one standard deviation increase in wage duration decreases the response in TFP by 1.1 percent for a one percent increase in GDP. As anticipated by the model, output is less cyclical for the stickier wage industries, while inputs are significantly more cyclical. Greater wage stickiness is now associated with a less cyclical wage; but this effect is small and not statistically significant.

6. Conclusion

We start from what we view as a reasonable depiction of wage setting, with wages sticky for most current workers, but flexible for new hires. We depart from standard treatments of sticky wages by allowing worker effort to respond to the wage being too high or low. We see this as consistent with firms making fairly frequent choices for production and work assignments, more frequent than wages are rebargained. We show that if wages of matched workers are stuck too high in a recession, then firms will require more effort. In turn, this lowers the value of additional labor, reducing new hiring. If we further constrain choices for effort to be common across worker vintages, we find that the model generates a great deal of wage inertia—for our benchmark calibration, aggregate wages depart from its flexible wage counterpart for 16 quarters, even though all wages have been renegotiated after 4 quarters. For our preferred model, with common effort, the volatility of unemployment relative to labor productivity is considerably increased. The countercyclical response in effort causes a greater response in unemployment to a given sized shock to labor demand, while partially masking the impact of that shock on labor productivity. Lastly, we construct measures of

wage stickiness across 60 sectors of the economy. We find that sectors with stickier wages do show more countercyclical TFP, together with more procyclical inputs. Though they fail to show more countercyclical wage rates.

The acyclicity of productivity, compared to the size of fluctuations in employment and hours, is especially notable for recent recessions. There have been several related changes in the workplace that have arguably made it easier for firms to ask more of workers in downturns. For one, a much greater share of workers are now paid by salary, rather than hourly. This means the real pay of workers can be reduced by asking for more hours, at a given pay, without expanding exertion per hour. Anger (2011) shows that extra unpaid hours are highly countercyclical for salaried workers. Secondly, the share of union workers has sharply declined, possibly providing greater flexibility for firms to adjust demands on workers in response to economic conditions. Schmitz (2005) presents an example from ore mining where relaxing terms in union contracts led to a dramatic change in work rules and productivity.

Table 1: Benchmark Parameter Values

Parameter	Description
$T = 4$	Duration of wage contract
$\alpha = 0.64$	Labor share in production function
$\beta = 0.99$	Discount factor
$\gamma = 1.0$	Reciprocal of labor supply elasticity
$\delta = 0.04$	Job separation rate
$\chi = 0.6$	Scale parameter in matching function
$R = r + d = 0.035$	User cost of capital
$\rho_z = 0.95$	Persistence of aggregate productivity
$\sigma_z = 0.007$	Std. dev. of innovation to aggregate productivity
$\log \bar{z} = -7.0821$	Normalization of output to one
$\psi = 0.6826$	Scale parameter for utility from leisure
$b = 0.154$	Unemployment insurance benefits
$\kappa = 0.04754$	Vacancy posting cost

Table 2: KLEMS Industries

INDUSTRY	NAICS Code	VA Share	Calvo Frequency	Error Rate
Crop and Animal Production	111,112	1.6	0.24	0.20
Forestry and Fishing	113-115	0.4	0.27	0.25
Oil and Gas Extraction	211	1.1	0.28	0.25
Mining, except Oil and Gas	212	0.4	0.23	0.25
Support Activities for Mining	213	0.3	0.22	0.25
Utilities	22	2.7	0.27	0.27
Construction	23	6.2	0.25	0.21
Food, Beverage, and Tobacco	311,312	2.16	0.32	0.21
Textile Mills and Textile Products	313,314	0.4	0.24	0.19
Apparel and Leather products	315,316	0.4	0.26	0.21
Wood products	321	0.4	0.31	0.17
Paper Products	322	0.9	0.32	0.21
Printing and Related Activities	323	0.6	0.26	0.23
Petroleum and Coal products	324	0.9	0.33	0.14
Chemical products	325	2.4	0.31	0.27
Plastics and Rubber products	326	0.9	0.29	0.20
Nonmetallic Mineral Products	327	0.	0.31	0.24
Primary Metals	331	0.7	0.24	0.23
Fabricated Metal products	332	1.6	0.30	0.19
Machinery	333	1.6	0.28	0.22
Computer and Electronic products	334	2.2	0.30	0.24
Electrical Equipment and Appliances	335	0.7	0.31	0.23
Transportation Equipment	336	2.5	0.31	0.26
Furniture and related products	337	0.4	0.33	0.20
Miscellaneous Manufacturing	339	0.8	0.30	0.24
Wholesale Trade	42	6.7	0.29	0.26
Retail Trade	44,45	8.0	0.28	0.22
Air Transportation	481	0.5	0.28	0.29
Rail Transportation	482	0.4	0.28	0.26

Water Transportation	483	0.1	0.25	0.27
Truck Transportation	484	1.3	0.28	0.21
Transit and Ground Passenger Transportation	485	0.2	0.23	0.27
Pipeline Transportation	486	0.1	0.25	0.21
Other Transportation	487,488,492	1.0	0.33	0.22
Warehousing and Storage	493	0.4	0.30	0.17
Publishing Industries	511,516	1.4	0.28	0.25
Motion Picture and Recording Industries	512	0.5	0.27	0.30
Broadcasting and Telecommunications	515,517	3.1	0.30	0.27
Information and Data Processing Services	518,519	0.6	0.32	0.26
Credit Intermediation and Related Activities	521,522	3.7	0.28	0.28
Securities, Commodities, and Investments	523	2.1	0.26	0.26
Insurance Carriers and Related Activities	524	2.7	0.30	0.29
Funds, Trusts, and other Financial Vehicles	525	0.9	0.26	0.26
Real Estate	531	4.9	0.28	0.25
Rental and Leasing Services	532,533	1.7	0.25	0.27
Legal Services	5411	1.9	0.24	0.26
Miscellaneous Professional, Scientific and Technical Services	5412- 5414,5416- 5419	5.6	0.28	0.26
Computer System Design and Services	5415	1.2	0.27	0.28
Management of Companies and Enterprises	55	2.3	0.28	0.26
Administrative and Support Services	561	3.2	0.28	0.23
Waste Management and Remediation Services	562	0.4	0.27	0.25
Educational Services	61	0.2	0.31	0.25
Ambulatory Health Care Services	621	3.9	0.27	0.21
Hospitals, Nursing, Residential Care Facilities	622,623	1.4	0.32	0.22
Social Assistance	624	0.3	0.32	0.23
Performing Arts, Spectator Sports, Museums, and Related Activities	711,712	0.4	0.29	0.26
Amusements, Gambling, and Recreation	713	0.5	0.27	0.25
Accommodation	721	0.9	0.30	0.19
Food Services and Drinking Places	722	2.0	0.29	0.23
Other Services, except Government	81	2.6	0.27	0.23

Table 3: Industry Wage and TFP Fluctuations

	Dependent Variable			
	TFP for Value Added		TFP for Gross Output	
Wage	0.54 (0.04)	-0.08 (0.09)	0.28 (0.02)	-0.05 (0.04)
Wage*Labor's Share		1.13 (0.15)		1.16 (0.12)

Notes: Sample includes 1439 observations—60 industries by 24 years, with one invalid observation. TFP measures are adjusted for estimated capital utilization. TFP and real wage adjusted for compositional changes. Regression includes a full set of year dummies, so wage and TFP measures capture **relative** industry wages and TFP. Industry observations are weighted by its relative value added.

Table 4: Frequency of Wage Changes SIPP, 1990-2011

	4- month Freq	8-month Freq	Error Rate (Calvo)	Calvo 4-mo Parameter	Taylor 4-mo Parameters	New Hire Rate (%)
1990-1993 Panels (Approx. 1990-1995)	0.68	0.76	0.34	0.26	0.20	6.5 (9.1)
1996 Panel (Approx. 1996-1999)	0.75	0.85	0.36	0.39	0.28	7.6 (10.1)
2001 Panel (Approx. 2001-2004)	0.76	0.84	0.38	0.34	0.25	8.3 (10.4)
2004 Panel (Approx. 2004-2007)	0.39	0.55	0.07	0.28	0.22	8.4 (10.2)
2008 Panel (Approx. 2008-2011)	0.29	0.40	0.05	0.19	0.16	7.1 (8.7)
Average over all Panels	0.57	0.69	0.25	0.29	0.22	7.5 (9.6)

Notes: Observation per panel for calculating 4-month frequency of wage change by panel are respectively, top to bottom, 347,249, 135,133, 82625, 109,743, and 105578 for a total of 780,328 persons. The total sample for calculating 8-month changes is smaller at 575,314, while for calculating the new hire rate it is larger at 905,116. Observations are weighted both by the SIPP sampling weight and by the workers relative monthly earnings. The exception is that for the new hire rate we also report, in parentheses, the rate only weighting by the SIPP weight. In calculating the Calvo and Taylor parameters we actually use the 4-month rate for 8-month stayers; but this makes little difference.

Table 5: Industry Cyclicity by Wage Stickiness

	Dependent Variable		
	Inputs	TFP	Wage
	All 60 Industries		
GDP	1.18 (.05)	0.18 (.11)	0.11 (.07)
GDP*Stickiness	0.17 (.04)	-0.29 (.10)	0.22 (.06)
	30 Industries With Lower Labor Share		
GDP	0.78 (.05)	-0.14 (.20)	0.03 (.13)
GDP*Stickiness	0.13 (.04)	-0.20 (.15)	0.22 (.09)
	30 Industries With Higher Labor Share		
GDP	1.41 (.07)	0.40 (.13)	0.15 (.07)
GDP*Stickiness	0.15 (.07)	-0.45 (.14)	0.20 (.08)

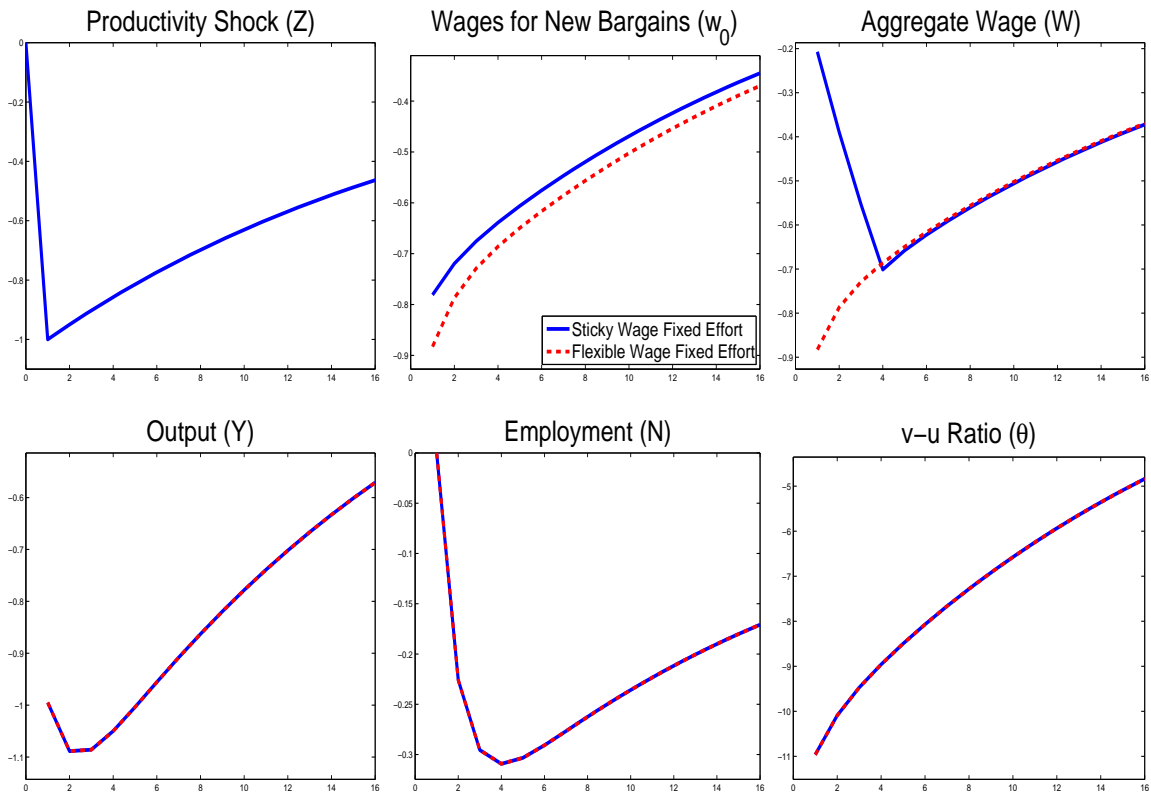
Notes: Standard errors are in parentheses. GDP is the HP-filtered aggregate real GDP. Stickiness is the Calvo implied duration of wages in the industry (in months) minus the mean across industries of 14.4 months. TFP is value added TFP adjusted for capital utilization. Inputs are labor and capital. All regressions weight observations by industry value added share. Durable industries are those with goods having expected life of at least one year.

Table 6: Cyclicality by Stickiness for Goods Industries

	Dependent Variable		
	Inputs	TFP	Wage
	All 24 Goods Industries		
GDP	1.75 (.07)	0.40 (.20)	0.01 (.11)
GDP*Stickiness	0.30 (.04)	-0.64 (.13)	0.02 (.07)
	12 Goods Industries With Lower Labor Share		
GDP	0.83 (.08)	-0.45 (.36)	0.01 (.20)
GDP*Stickiness	0.19 (.04)	-0.47 (.20)	0.19 (.11)
	12 Goods Industries With Higher Labor Share		
GDP	2.43 (.10)	1.24 (.22)	0.11 (.12)
GDP*Stickiness	0.16 (.07)	-1.13 (.16)	-0.12 (.09)
	14 Durable Goods Industries		
GDP	2.37 (.09)	0.94 (.21)	0.05 (.11)
GDP*Stickiness	0.21 (.06)	-1.00 (.15)	-0.10 (.08)

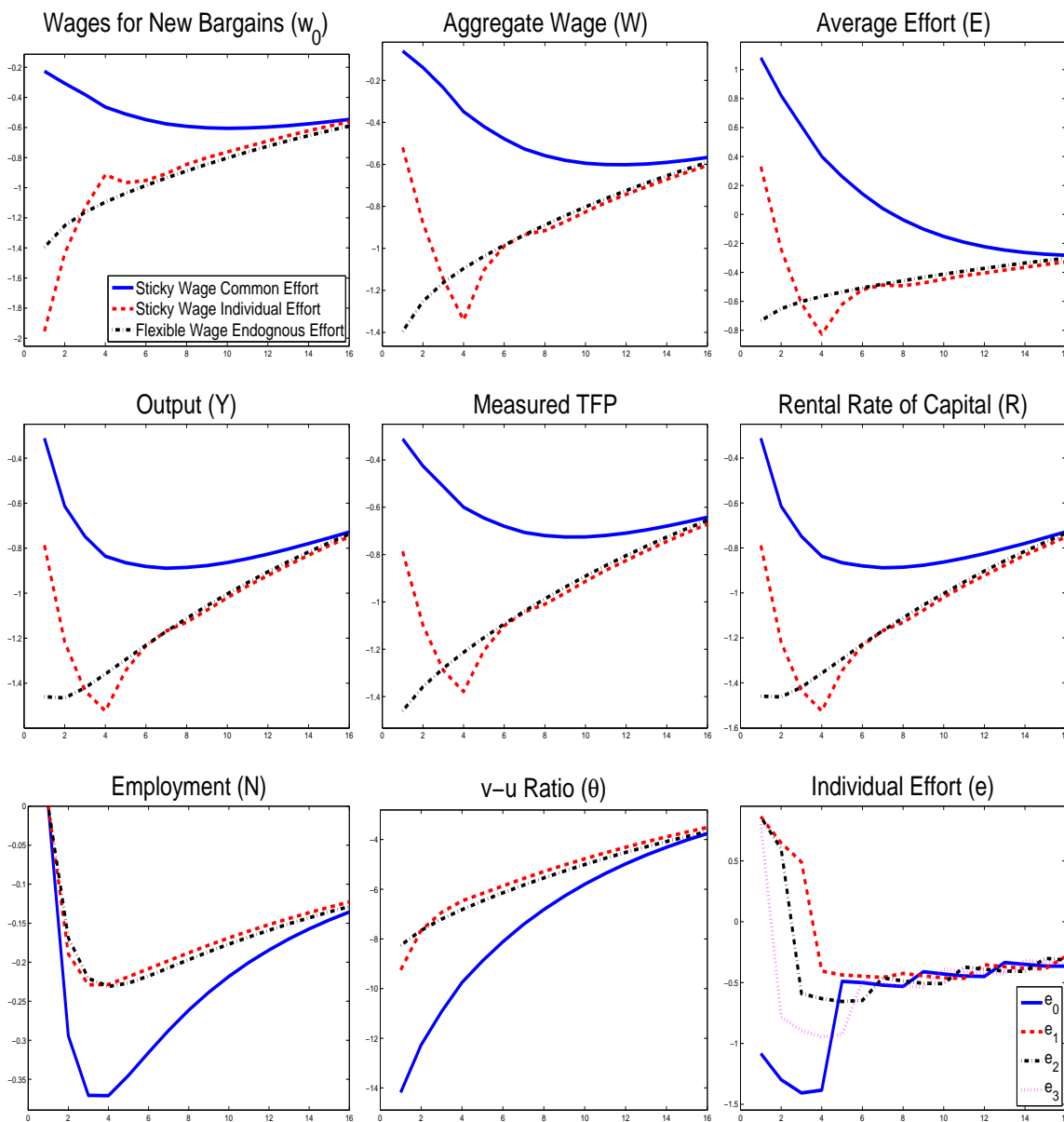
Notes: GDP is the HP-filtered aggregate real GDP. Stickiness is the Calvo implied duration of wages in the industry (in months) minus the mean across industries of 14.4 months. TFP is value added TFP adjusted for capital utilization. Inputs are labor and capital. All regressions weight observations by industry value added share. Durable industries are those with goods having expected life of at least one year.

Figure 1: Model with Fixed Effort



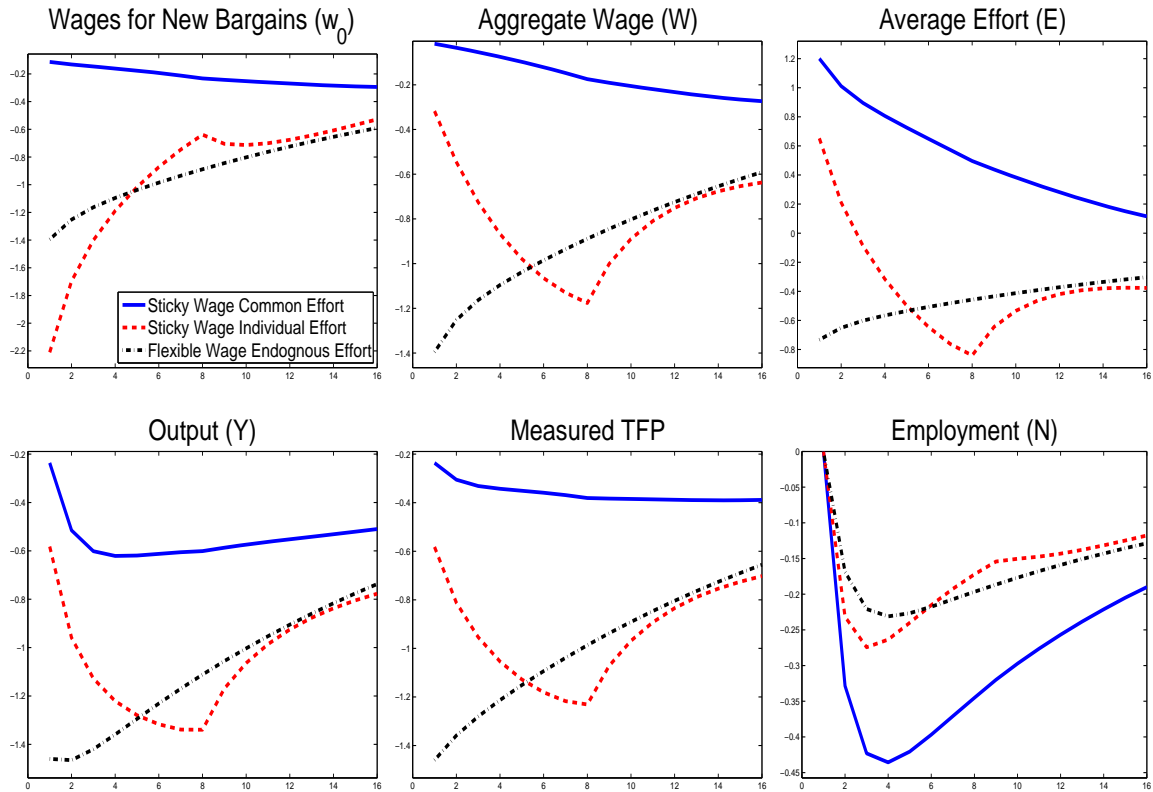
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dashed line (---) represents the model with flexible wages. The solid line represents the model with sticky wages.

Figure 2: Model with Variable Effort



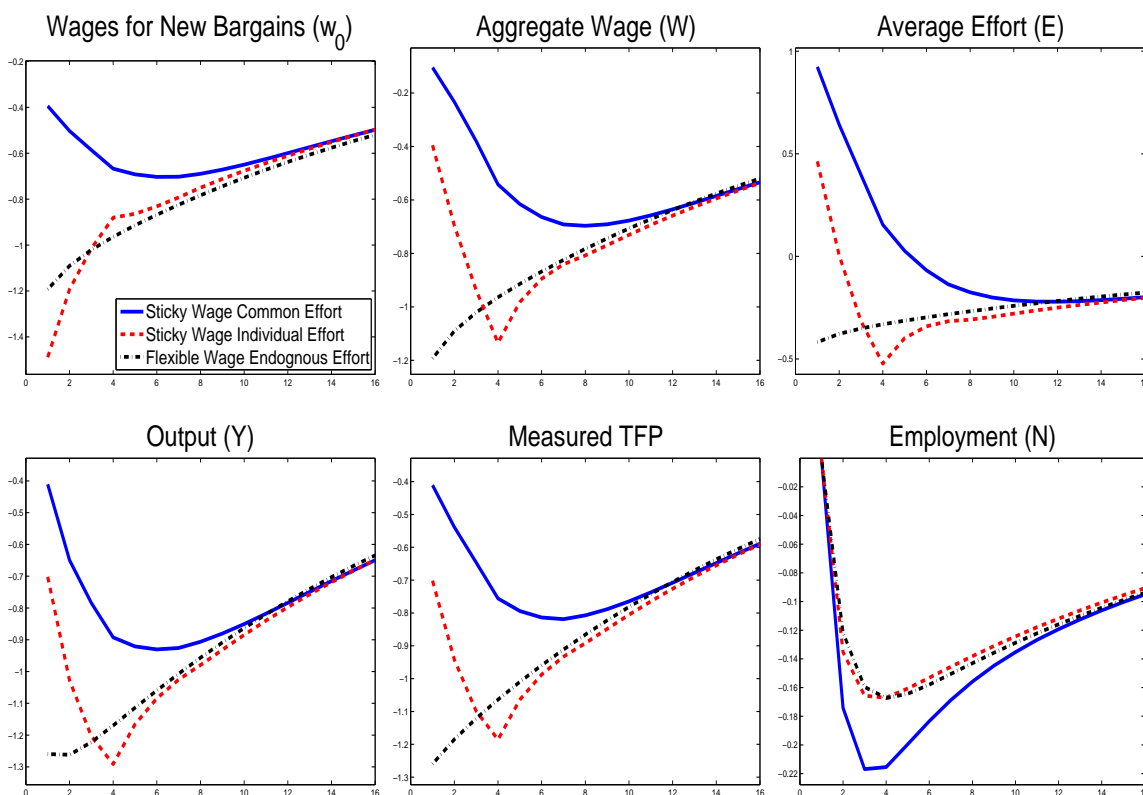
Notes: Productivity decreases by 1% in period 1 autocorrelation of 0.95. The dash-dot line (— · —) represents the model with flexible wages. The dashed line (---) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice. All models feature $\gamma = 1.0$, $T = 4$, and $\alpha = 0.64$.

Figure 3: Model with a Longer Contract Length ($T = 8$)



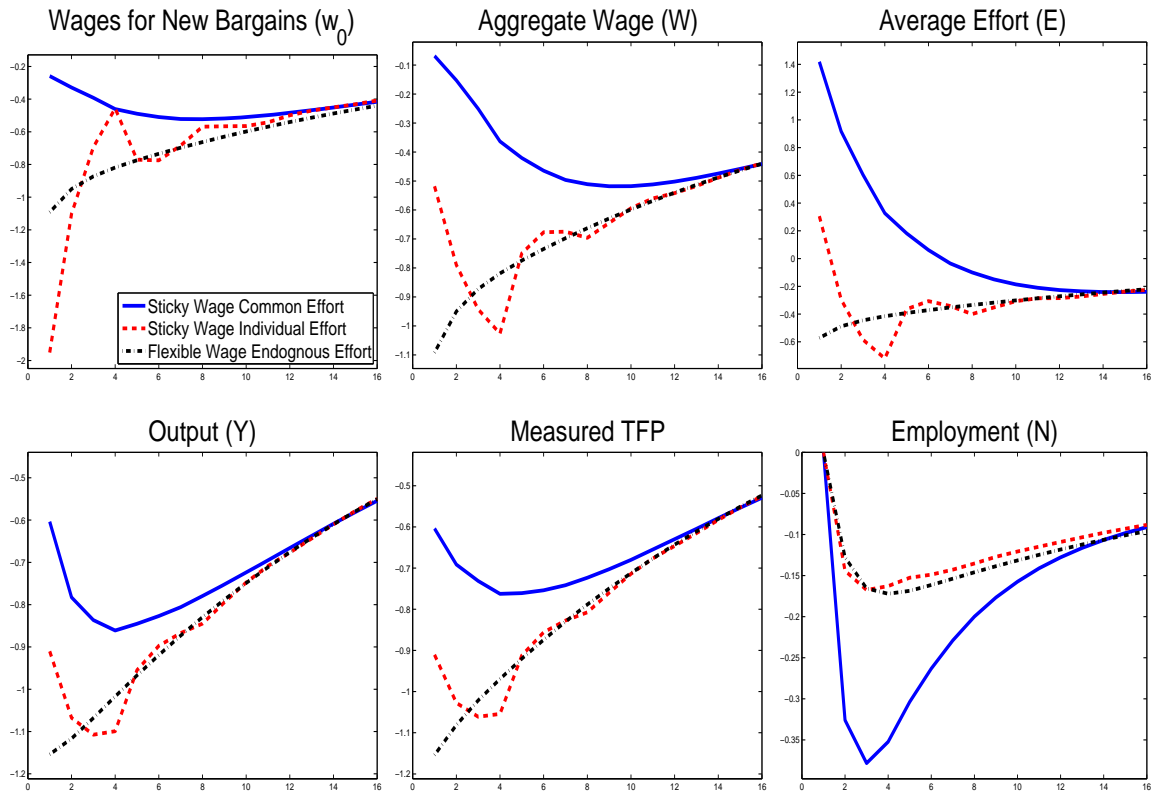
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dash-dot line (—.) represents the model with flexible wages. The dashed line (--) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice. All models feature a longer contract length $T = 8$.

Figure 4: Model with a Smaller Frisch Elasticity of Effort ($\gamma = 2$)



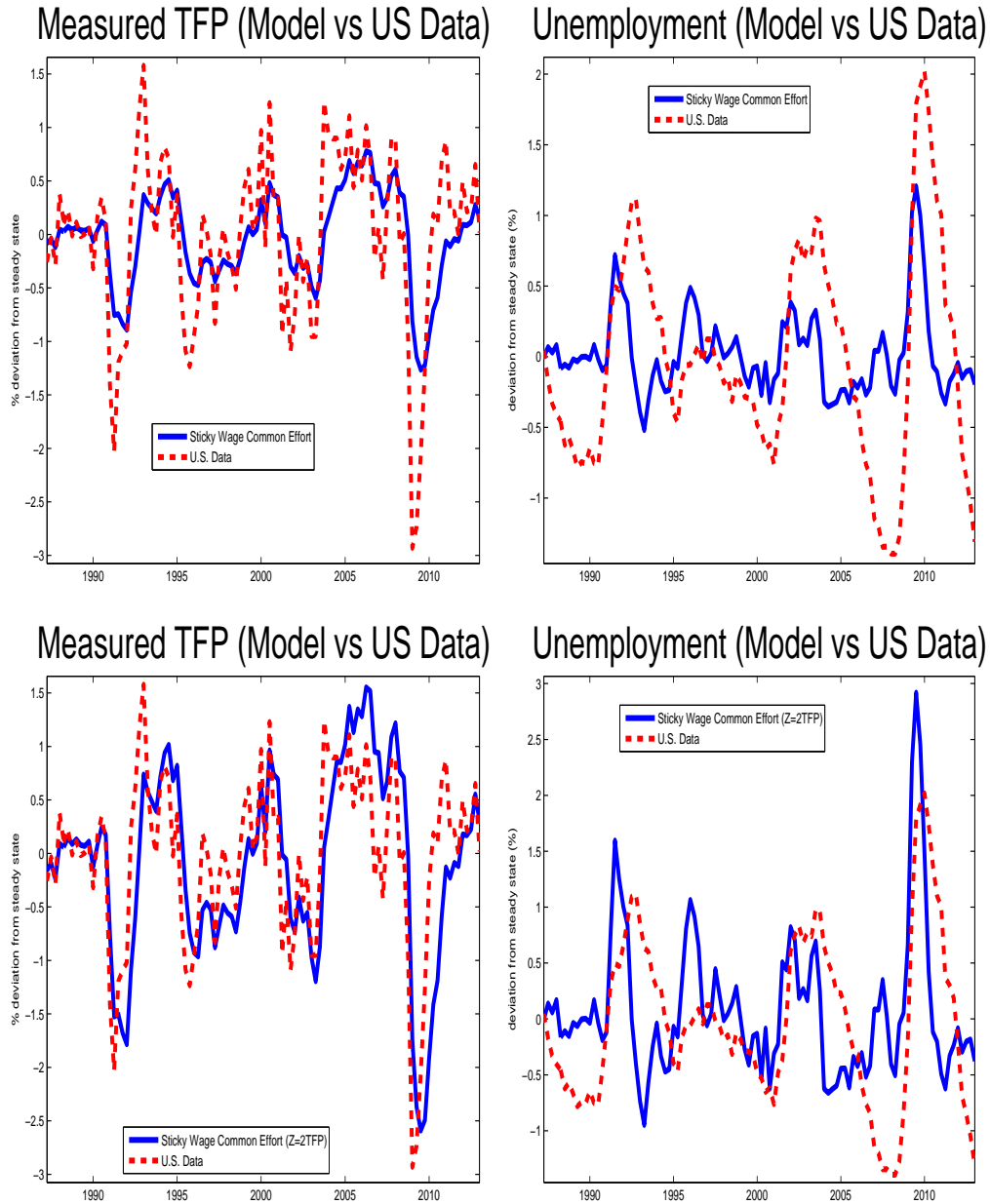
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dash-dot line (—.) represents the model with flexible wages. The dashed line (--) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice. All models feature a smaller Frisch elasticity (0.5) of labor effort supply: $\gamma = 2$.

Figure 5: Model with Smaller Labor Demand Elasticity ($\alpha = 0.28$)



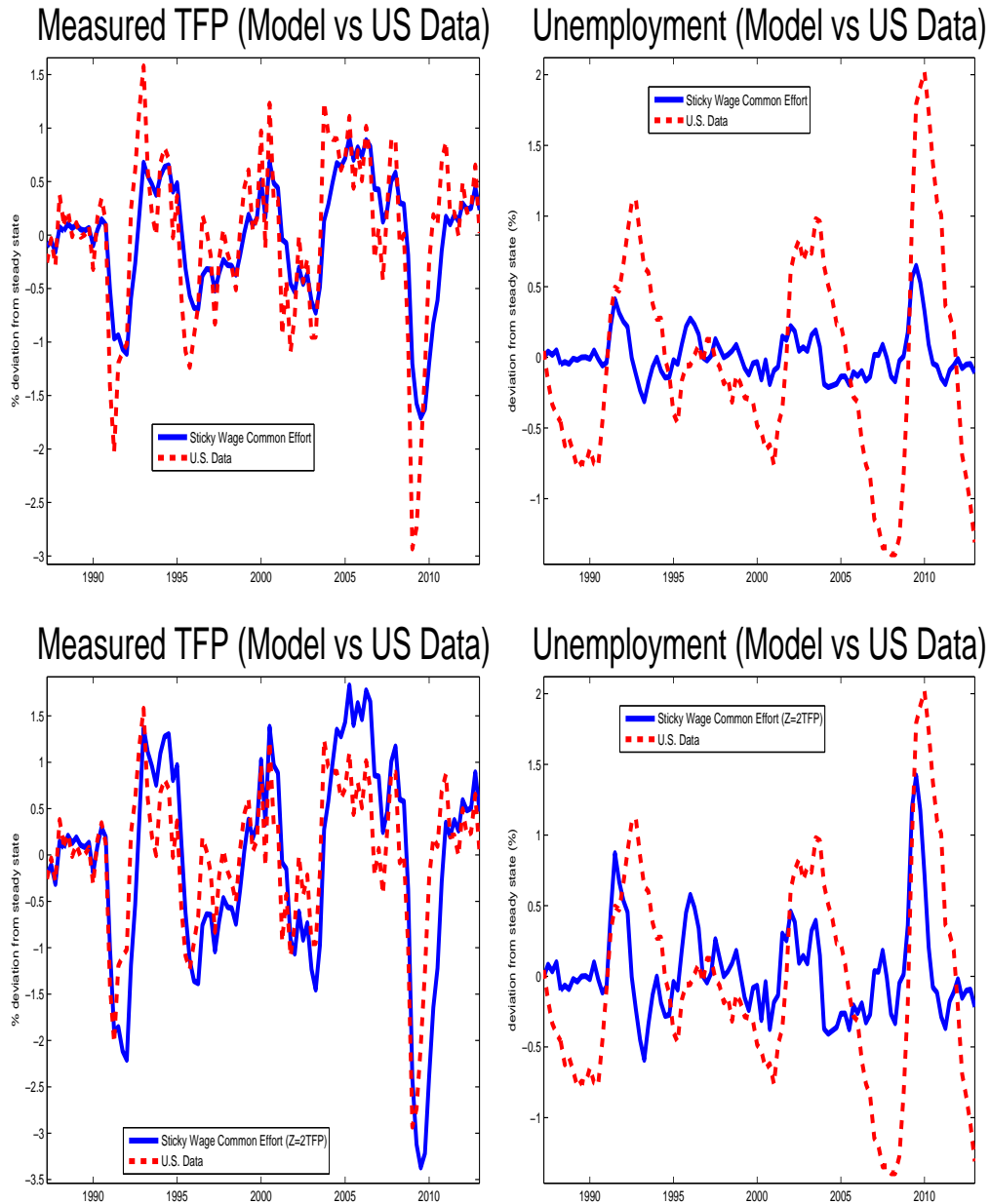
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dash-dot line (—.) represents the model with flexible wages. The dashed line (--) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice. All models feature a flatter short-run labor demand schedule ($\alpha = 0.28$).

Figure 6: TFP and Unemployment Rates: U.S. Data vs. Model ($\gamma = 1$)



Notes: In the upper panel, we use the actual time series of (detrended) TFP from the U.S. economy (1987 : 1Q – 2012 : 4) as a productivity shock. In the lower panel, for productivity shock, we multiply the US TFP by 1.8 (i.e., $z_t = 1.8 \times TFP_t^{US}$).

Figure 7: TFP and Unemployment: U.S. Data vs. Model ($\gamma = 2$)



Notes: In the upper panel, we use the actual time series of (detrended) TFP from the U.S. economy (1987 : 1Q – 2012 : 4Q) as a productivity shock. In the lower panel, for the productivity shock, we use the US TFP multiplied by 1.42 (i.e., $z_t = 1.42 \times TFP_t^{US}$) to match the volatility of the measured TFP in the data.

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