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 effort to respond to the wage being too high or low. Shimer (2004) 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 more effort, lowering the value of additional labor and reducing new hiring.

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1. Introduction

There is much evidence that wages are sticky within employment matches. For instance, Barattieri, Basu, and Gottschalk (2014) 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 more procyclical than for those in continuing jobs.

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 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.

In our model wage stickiness acts to raise productivity in a recession, relative to a flexible or standard sticky wage model. Thus it helps to understand why labor productivity shows so little procyclicality, especially for the past 25 plus years (e.g., Van Zandweghe, 2010).[1] It is also consistent with an array of anecdotal evidence that firms have required more tasks from their workers since the onset of the Great 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 dictates 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,

[1] For 1987 to 2012 the correlation between labor hours and labor productivity equals -0.58 (from BLS data on multifactor productivity, series quarterly HP-filtered). In particular, during the seven quarters of the NBER-defined Great Recession hours declined by 10 percent compared to only a 7 percent decline in real output. For the prior recession (beginning 2001.I) labor productivity similarly increased by 4 percent.

driving up effort and wages for the next cohort of new hires, and so forth. By generating (counter)cyclicality in effort, this model can make vacancies and new hires considerably more cyclical.

There is only sparse direct evidence on cyclicality of worker effort. Anger (2011) studies paid and unpaid overtime hours in Germany for 1984 to 2004. She finds that unpaid overtime (extra) hours are highly countercyclical. This is in sharp contrast to cyclicality in paid overtime hours. Quoting the paper: "Unpaid hours show behavior that is exactly the opposite of the movement of paid overtime." Lazear, Shaw, and Stanton (2012) examine data on productivity of individual workers at a large (20,000 workers) service company for the period June 2006 to May 2010, bracketing the Great Recession. At this company a computer keeps track of worker productivity. They find that effort is highly countercyclical, with an increase in the local unemployment rate of 5 percentage points associated with an increase in effort of 3.75%.[2]

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 cyclicality 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. 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 (TFP) is more procyclical in industries with more flexible wages; and this impact is much greater for industries where labor is especially important as a factor of production. These

[2]Schor (1987) reports on the cyclicality 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.

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 a 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:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big\{ c_t + \psi \frac{(1-e_t)^{1-\gamma} - 1}{1-\gamma} \Big\},$$

  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 wage w_t and exerts 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 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 Nash bargaining beginning with the first period employed and remain fixed for T periods, provided the match survives the exogenous match separation shocks. Matches can be categorized into T cohorts according to the age of contract (i.e., the number of periods since the wage was negotiated). The number of workers whose contract is j periods old is denoted by $N_{j,t}$, where $j = 0, 1, \cdots, T-1$. 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 Nash bargaining 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 constant returns to scale in aggregate capital K_t, and labor L_t, which sums efforts of all workers:

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

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

- **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 is 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 a function of only labor market tightness θ $(= v/u)$: $p(\theta_t) = \chi\theta_t^{1/2}$ and $q(\theta_t) = \chi\theta_t^{-1/2}$. Finally, we assume that each period existing matches break at the exogenous rate δ and that firms posts vacancies at 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.[3] For the matches whose contracts are already specified, i.e., for $j = 0, 1, \cdots, T-2$:

$$\begin{aligned} W_j(w_j; z, \mu) = w_j + \psi\frac{(1-e)^{1-\gamma} - 1}{1-\gamma} \\ + \beta\Big\{(1-\delta)\mathbb{E}\big[W_{j+1}(w_j; z', \mu')|z\big] + \delta\mathbb{E}\big[U(z', \mu')|z\big]\Big\}. \end{aligned} \tag{2}$$

subject to

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

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

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

$$\begin{pmatrix} w_0' \\ w_1' \\ \vdots \\ w_{T-1}' \end{pmatrix} = \begin{pmatrix} w^*(z', \mu') \\ w_0 \\ \vdots \\ w_{T-2} \end{pmatrix}, \tag{5}$$

[3]In the definition of W_j, we explicitly put w_j in the list of state variables, although it is part of μ, to emphasize the sticky wage contract which was determined j periods earlier and persists in the next period. The value of a matched job J_j is similarly defined below.

$$\begin{pmatrix} N_0' \\ N_1' \\ \vdots \\ N_{T-1}' \end{pmatrix} = \begin{pmatrix} (1-\delta)N_{T-1} + M(u,v) \\ (1-\delta)N_0 \\ \vdots \\ (1-\delta)N_{T-2} \end{pmatrix}, \tag{6}$$

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., $j = T-1$:

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

The value to the unmatched (unemployed) worker is:

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

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

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

whereas, for a job that will negotiate the wage in the next period (i.e., $j = T-1$)

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

subject to (3) and (4).

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

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

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

$$w^*(z, \mu) = \underset{w}{\operatorname{argmax}} \Big(J_0(w; z, \mu)\Big)^{1/2} \Big(W_0(w; z, \mu) - U(z, \mu)\Big)^{1/2}. \tag{12}$$

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

$$J_0(w^*; z, \mu) = W_0(w^*; z, \mu) - U(z, \mu). \tag{13}$$

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:

$$e_j^*(w_j, z, \mu) = \underset{e_j}{\operatorname{argmax}} \Big(J_j(e_j; w_j, z, \mu)\Big)^{1/2} \Big(W_j(e_j; w_j, z, \mu) - U(z, \mu)\Big)^{1/2} \tag{14}$$

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

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

for $j = 0, 1, \cdots, T-1$. 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 vary work rules so much 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 a model (our preferred benchmark) with bargaining over a common effort level.

When workers must work a common effort level, we assume that this effort, $e(z, \mu)$, 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:

$$e^*(z, \mu) = \underset{e}{\operatorname{argmax}}\, J(e; z, \mu)^{1/2} W(e; z, \mu)^{1/2}, \tag{16}$$

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

$$J(e^*;z,\mu)\psi(1-e^*)^{-\gamma} = W(e^*;z,\mu)\alpha z k^{1-\alpha}. \tag{17}$$

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 T periods, is negotiated according to (12). Once they engage in production, workers negotiate the common effort level according to (16). The wage bargaining treats the parties as sufficiently small that they ignore any impact of their bargained wage on the anticipated effort level. That is, the negotiated wage anticipates the future negotiated effort levels, but does not attempt to influence these choices.[4]

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), $r + d$, of 3.5%.

Key parameters for the impact of wage stickiness on 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

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

$$e^*(z,\mu) = \underset{e}{\operatorname{argmax}}\ \Pi_{j=0}^{T-1}\left(J_j(e;z,\mu)^{\frac{1}{2}}\left(W_j(e;z,\mu) - U(z,\mu)\right)^{\frac{1}{2}}\right)^{\frac{N_j}{N}}.$$

This objective function is the geometric mean of the objective functions in individual Nash bargaining 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 equals the ratio of the harmonic mean of surpluses of workers to the harmonic mean of surpluses of jobs. Although these ratios are not exactly equal in the economy subject to fluctuations, our simulations suggest they do not diverge very far. For our common effort model, 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 carry the size of each cohort, i.e., $N_{j,t}/N_t$ for $j = 0, 1, \ldots, T-1$ for all t to compute the harmonic means. This dramatically increases the dimension of the state space, making it impractical to compute the equilibrium. Therefore, we only obtain and present results for the bargaining protocol (16).

labor demand schedule. In turn, this means higher effort from existing workers in a recession will crowd out more hiring. For our benchmark the 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 less elastic labor demand schedule (a lower value of 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.[5] This implies that the Frisch elasticity is $\frac{1}{\gamma}$. This elasticity is difficult 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 estimates 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 workweek 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. Schor (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 measure represents the ratio between actual effort and a standard level of intensity as defined by "time and motion" men. Schor 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 of 0.5.

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 vacancy posting cost (κ) is chosen to satisfy the free entry condition

[5] The steady state effort level reflects the utility parameter ψ, and other calibrated parameters, according to: $e = 1 - (\psi/\alpha)^{1/\gamma}\left(\frac{r+\delta}{1-\alpha}\right)^{\left(\frac{1-\alpha}{\alpha\gamma}\right)}$.

in (11). Given the steady-state wage w_{ss}, the unemployment benefit (b) is chosen so that the replacement rate (in terms of utility), $b \Big/ \left(w_{ss} + \psi \frac{(1-e)^{1-\gamma}-1}{1-\gamma} \right)$, equals 70%.

4. Results

We illustrate how our model with endogenous effort responds to an aggregate shock that affects labor demand using a negative productivity shock.

4.1. Impact of Sticky Wages with Fixed Effort

First, however, consider the impact of wage stickiness under fixed effort. Figure 1 shows model responses, with both flexible and sticky wages, to a one percent decrease in aggregate productivity. (The shock, shown in the first panel, persists with autocorrelation 0.95.). The next two panels show the wage responses, first for new matches or those re-bargaining, then for all workers. Wages of new bargains respond similarly under both flexible (denoted by "$--$") and sticky wages (denoted by "$-$"), 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 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. But after four quarters all wages will reflect the shock to productivity–so the aggregate wage coincides under flexible or sticky wages at that point.

The last panel of Figure 1 illustrates how employment responds 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 under fixed effort.

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, again to a one percent decrease in productivity (with autocorrelation of 0.95).

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; so 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 new hiring and employment. 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 cyclicality of the 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 newly-bargained wage actually responds more 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, new hires and employment drop more initially under sticky wages (panels 7 and 8), though admittedly this effect is quite 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 have such varying work rules across employees. 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 fourteen quarters—ten 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 of sticky wage workers and settling for a less than efficient bargaining for new wages. For our calibrations, the effort choice is dominated by the desire to obtain the possible effort level from the sticky-wage workers, with average effort increasing to nearly offset the negative 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 the wage for these workers is then stuck higher for the next three quarters, acting to generate a higher effort choice. 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 cyclicality of the rental rate of capital (panel 6). In turn, this exacerbates the cyclicality of vacancy creation, new hiring, and employment (panels 7 and 8). In particular, 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 cyclicality 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. Studies of payrolls at large firms (Altonji and Devereux, 2000, LeBow, Sachs, and Wilson, 2003) find that perhaps 20 percent of workers show no wage change even over a year. More recently, employing SIPP data, Barrattieri, Basu, and Gottschalk (2014) 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 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 hiring of new workers is directly linked to the short-run elasticity of the aggregate labor demand schedule. 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. 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 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 U.S. Data

Can our model help account for observed movements 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 treat BLS-measured TFP (H-P filtered) for 1987:1 to 2012:4 as productivity shocks. For comparison, we also plot the actual time series of BLS-TFP and the unemployment rate (in dotted lines). The unemployment rate from the model under-predicts cyclicality 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.

For this reason, we multiply the BLS-TFP fluctuations by 1.92 so that the standard deviation of the model-generated TFP matches that in the data. Under these adjusted productivity shocks, the model now generates much more volatility in unemployment. In terms of standard deviation, the model now accounts for a little more than two-thirds of unemployment volatility (0.53% in the model vs. 0.75% in the data). Thus our model has a relatively small Shimer (2005) puzzle, despite the replacement flow value of unemployment being calibrated to only 70 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 cyclicality of the underlying shock, so that unemployment fluctuations look larger relative to those in productivity.

We repeat the same experiment with a Frisch elasticity of 0.5 in Figure 7. Effort now becomes less responsive, causing the model to generates less volatile unemployment. Because effort is less counter-cyclical, matching volatility of TFP from the data requires feeding in productivity shocks that multiply BLS-TFP fluctuations by 1.42. Under the Frisch of 0.5, the model accounts for just over one-fourth of unemployment volatility in the data. (The model's standard deviation for unemployment becomes 0.20%.) 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 knowing 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 shocks to productivity, as well as their correlation with other shocks, it is hard to evaluate the model based on the cyclicality of measured productivity.

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 subsection shows that there is a strong correlation between relative industry wage movements and relative industry TFP movements that is present only to the extent labor is important as a factor of production. The second subsection employs data from the Survey of Income and Program Participation (SIPP) to measure wage stickiness across industries. We then examine how hours, TFP, and wages respond cyclically for industries with more versus less sticky wages.

5.1. Cross-Industry Wage and Productivity Patterns

The U.S. KLEMS provides data for output, inputs, and factor costs annually from 1987 to 2010 for 18 manufacturing and 42 non-manufacturing sectors. Industries are listed in Table 2, together with their relative values added. The data appendix describes how we calculate value-added TFP from KLEMS data. It also describes how we adjust for the impact of procyclical utilization of capital and cyclical variations in the composition of the workforce.

Our focus is on cyclical movements in wages and productivity; so we HP-filter the series, with the filter defined separately for each industry, using smoothing parameter of 6.25 suggested by Ravn and Uhlig (2002) 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 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.

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, the balance of the paper focuses on 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.

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's wage movement with its labor share in value added. (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 1.12 percent, with standard error 0.30 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 slight decrease in hours of 0.05 percent (with standard error of 0.02 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.

5.2. 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). The data appendix describes our SIPP sample and variable constructions. We calculate frequency of wage changes over the four month interval between interviews for workers who remain with the same employer. Employed respondents report monthly earnings. In addition, a little over half of those working report an hourly rate of pay. We also calculate a weekly wage for each worker, dividing monthly earnings by weeks worked. We define a worker's wage as not changing if any of these three measures remains the same across the surveys.

A concern with using micro data on wage changes is that measurement errors will contribute to the reported frequency. Barattieri, Basu, and Gottschalk (2014, BBG henceforth), for instance, deal with measurement error by keeping only wage changes that can be viewed as a time-series structural shift for the individual's wage series. BBG report that the procedure removes 63% of wage changes for hourly-paid workers. We also allow for measurement error in the individual wages. But we adopt a simpler and, at least ex post, somewhat more conservative representation for the measurement error. We make the following assumptions: (i) The probability of measurement error is the same for all individuals within an industry within a panel of the SIPP. This implies the probability is independent of a true wage change or a prior measurement error. (ii) There is zero probability of a true wage change, followed by an exactly opposite true wage change, 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 of a wage change, and a Taylor assumption that the 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_4 and Δ_8, are respectively:

- $\Delta_4 = \alpha + (1 - \alpha_c)(2\phi - \phi^2)$
- $\Delta_8 = (2\alpha_C - \alpha_C^2) + (1 - 2\alpha_C - \alpha_C^2) * (2\phi - \phi^2)$

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 chage are α_C versus $(2\alpha_C - \alpha_C^2)$. Given measures for Δ_4 and Δ_8, we can calculate α_C:[6]

$$\alpha_C = \frac{\Delta_8 - \Delta_4}{1 - \Delta_4}. \tag{18}$$

If we adopt the Taylor assumption instead, that Taylor frequency is related to the Calvo calculated frequency by $\alpha_T = \alpha_C/(1 + \alpha_C)$.[7]

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. 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. 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, 69% over 4 months and 78% over eight. 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 69% frequency over 4 months would imply we should see a 90% frequency over 8 months, rather than 78%.

[6] And ϕ solves the quadratic equation: $0 = \phi^2 - 2\phi + \frac{2\Delta_8 - \Delta_4^2 - \Delta_4}{1 - \Delta_4}$.

[7] The values for Δ_4 and Δ_8 from the text stay intact, except the probability of a true change over two periods equals $2\alpha_T$, where α_T is the 4-month Taylor probability of a true change. This assumes $\alpha_T < 1/2$, which holds for our estimates.

Our approach rationalizes the observed rates under Calvo if the true 4-month frequency is 0.30 and the probability of measurement error at each survey equals 0.33. Under the Taylor assumption, because it exhibits an increasing hazard of wage change, the relative frequencies at 4 and 8 months imply greater measurement error and a smaller 4-month true frequency of 0.23.

There are considerable differences in frequencies of wage changes across the 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 modestly more flexible wages. The Calvo parameters are calculated at 0.38 and 0.33 for the 1996 and 2001 panels. The last two panels, 2004 and 2008, show much lower rates of wage changes. Our calculations explain the drop in frequencies primarily by a fall in the measurement error rate. Beginning in 2004, the Census carries much more employment information forward from the household's prior interview, conditional on a respondent stating that their employment and earnings are basically unchanged from four months prior. This raises the concern that true wage changes, especially small ones, are not captured by the survey. For this reason, we base our benchmark estimates of wage stickiness on the 1990 through 2001 SIPP panels. But results in subsequent Table 5 are little affected if we incorporate the 2004 and 2008 panels.

The bottom of the table aggregates the panels. Aggregating through the 2001 panel, the calculated Calvo and Taylor parameters are 0.33 versus 0.25. If we invert these 4-month frequencies and multiply by the period's length (4-month) we get implied durations of wages of 12 months under Calvo and 16 months under Taylor. Papers in the literature that calibrate wage stickiness typically choose a value of 12 months; so these values are close to those.

The results in Table 4 combine hourly-paid and salaried workers. But we find similar frequencies across the groups–a Calvo parameter of 0.35 for hourly versus 0.31 for salaried. The observed frequency of wage change is higher for salaried workers, but our approach interprets this as reflecting twice as common of measurement errors for salaried workers.[8]

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

[8]BBG's (2014) approach, employing the 1996 SIPP panel yields stickier wage rates. Our estimated rates for the 1996 panel are 40 to 50 percent higher than their preferred estimate for hourly workers. It is nearly ten times higher than their estimate for salaried workers; but BBG put primary emphasis on their estimates for hourly workers.

rate varies from lows of 0.18, implying duration of 22 months, for mining, mining support industries, and water transportation to highs of 0.40, implying duration of 10 months, for petroleum and coal products, wood products, and paper products.[9]

5.3. Industry Wage Flexibility and Cyclicality 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's total hours (employment times workweek), TFP, and relative wage on the aggregate cycle (HP-filtered real GDP) interacted with stickiness of the wage. Industry TFP is corrected for fluctuations in capital utilization; industry TFP and real wage are adjusted for labor force composition. (See the appendix.) The measure of stickiness is the expected duration of wage in months, calculated under the Calvo assumption. All regressions include a full set of year dummies–so movements in all variables are interpreted as relative to aggregates. The regressions weight each observation by the industry's relative value added in that year. Standard errors are robust for correlated errors across time within industries and across industries within years (e.g., see Cameron, et al., 2011).

The top panel of Table 5 gives results for all 60 industries. Industries with stickier wages display more cyclical hours and less cyclical TFP. The standard deviation of wage duration equals 1.6 months; so the estimates imply that a one standard deviation increase in wage duration would increase the response in hours by about 0.13 percent and decrease the response in TFP by 0.22 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 they are not estimated very precisely. Furthermore, we do not see less cyclical wages for the stickier wage industries. In fact the sticky wage measure is associated with more cyclical wages; a one standard deviation increase in stickiness implies a 0.22 percent bigger wage response for a one percent increase in GDP. So this makes the data harder to interpret in light of the model.

[9]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 Bils, Klenow, and Malin (2012, BKM) is slightly negative at -0.1. 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 slightly negative at -0.1.

Real output, and therefore TFP, is presumably better measured for goods industries than services, as it is particularly difficult to measure output quality for services. For this reason, the second panel of the table restricts attention to the 24 industries that produce goods (agriculture, mining, construction, and manufacturing industries). We see that the impact of wage stickiness on cyclicality of TFP and hours is much stronger for these industries. A one standard deviation increase in wage duration would increase the response in hours by about one-quarter of a percent and decrease the response in TFP by two-thirds of a percent for a one percent increase in GDP. The estimated impact for TFP is statistically quite significant.

The next two panels breaks the goods industries by labor's share in value added. We partition at a labor share of two thirds, as this puts 12 industries into each group. 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 high-share industries -0.98 (s.e. 0.30) is four times that for those with low labor share, -0.25 (s.e. 0.08).

The bottom panel of Table 5 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 cyclicality of TFP. The estimates imply that a one standard deviation increase in wage duration decreases the response in TFP by 1.3 percent for a one percent increase in GDP. As anticipated by the model, hours are more cyclical for stickier wage industries, though the impact is much smaller than that for industry TFP. 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 re-bargained. 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 constrain choices for effort to be common across worker vintages then the model generates a great deal of wage inertia–for our benchmark calibration, aggregate wages depart from its flexible wage counterpart for 14 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 industries. We find that industries with stickier wages do show more countercyclical TFP. Though they fail to show more countercyclical wage rates.

The acyclicality of productivity, compared to the size of fluctuations in employment and hours, is especially notable for recessions over the past 25 or so years. 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.

References

[1] Altonji, J. G. and P. J. Devereux, 2000. The Extent and Consequences of Downward Nominal Wage Rigidity. Evidence from Panel Data. *Research in Labor Economics* 19, 383-431.

[2] Anger, S., 2011. The Cyclicality of Effective Wages within Employer–Employee Matches in a Rigid Labor Market. *Labour Economics* 18(6), 786-797.

[3] Basu, S. and J. Fernald, 1997. Returns to Scale in U.S. Production: Estimates and Implications. *Journal of Political Economy*, University of Chicago Press, 105(2), 249-83.

[4] Barattieri, A., S. Basu and P. Gottschalk, 2014. Some Evidence on the Importance of Sticky Wages. *American Economic Journal: Macroeconomics*, 6(1), 70-101.

[5] Bils, M. and J-O. Cho, 1994. Cyclical Factor Utilization. *Journal of Monetary Economics* 33(2), 319-354.

[6] Bils, M., P. Klenow and B. Malin, 2012. Testing for Keynesian Labor Demand. *Macroeconomics Annual*. 27, 311-349.

[7] Cameron, A. C., J. B. Gelbach and D. L. Miller, 2011. Robust Inference with Multiway Clustering. *Journal of Political Economy* 106, 867-896.

[8] Gorodnichenko, Y. and M. Shapiro, 2011. Using the Survey of Plant Capacity to Measure Capital Utilization. Working Papers 11-19, Center for Economic Studies, U.S. Census Bureau.

[9] Hall, R. E., 2009. Reconciling Cyclical Movements in the Marginal Value of Time and the Marginal Product of Labor. *Journal of Political Economy* 117(2), 281-323.

[10] Krusell, P., and A. Smith, 1997. Income and Wealth Heterogeneity, Portfolio Choice, and Equilibrium Asset Returns. *Macroeconomic Dynamics* 1, 387-422.

[11] Krusell, P., and A. Smith, 1998. Income and Wealth Heterogeneity in the Macroeconomy. *Journal of Political Economy* 106(5), 867-896.

[12] Lazear, E., K. Shaw and C. Stanton, 2012. The Value of Bosses. *NBER Working Papers* 18317, National Bureau of Economic Research, Inc.

[13] LeBow, D. E., R. E. Sachs, and B. A. Wilson, 2003. Downward Nominal Rigidity: Evidence from the Employment Cost Index. Advances in Macroeconomics 3(1).

[14] Pissarides, C., 2009. The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer? *Econometrica*, 77(5), 1339-1369.

[15] Ravn, M. and H. Uhlig, 2002. On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. *Review of Economics and Statistics*, 84(2), 371-375.

[16] Rogerson, R. and R. Shimer, 2010. Search in Macroeconomic Models of the Labor Market., in: O. Ashenfelter and D. Card, editors, Handbook of Labor Economics, volume 4A, 619-700.

[17] Schmitz, J., 2005. What Determines Productivity? Lessons From the Dramatic Recovery of the U.S. and Canadian Iron Ore Industries Following Their Early 1980s Crisis. *Journal of Political Economy,* 113(3), 582-625.

[18] Schor, J., 1987. Does Work Intensity Respond to Macroeconomic Variables? Evidence from British Manufacturing, 1970-86, Mimeo. (Harvard University, Cambridge, MA).

[19] Shimer, Robert, 2004. The Consequences of Rigid Wages in Search Models. *Journal of the European Ecomic Association (Papers and Proceedings)*, 2, 469-479.

[20] Shimer, R., 2005. The Cyclical Behavior of Equilibrium Unemployment and Vacancies. *American Economic Review*, 95(1), 25-49.

[21] Van Zandweghe, W., 2010. Why Have the Dynamics of Labor Productivity Changed? Federal Reserve Bank of Kansas City, *Economic Review*, Third Quarter, 5-28.

Appendix

A. Computational Algorithm

In this appendix, we briefly describe the algorithm employed to compute the equilibria of the models. We focus on the sticky-wage models with two different specifications regarding effort choice: 1) common effort and 2) individual effort. Our computational algorithm inherits the spirit of Krusell and Smith (1998) in that we approximate the distribution of matches (μ) by its first moments: the aggregate wage (Ω) and the aggregate employment (i.e., the number of total matches, N) in order to reduce the dimension of state space. Given the linear utility in consumption, the average wage is a good representation of the entire wage distribution in terms of welfare of workers. In particular, under the common effort case the bargaining between the firm and workers is over the weighted-average surplus of all matches. We also approximate the transition equation of the distribution, $\mu' = \mathbf{T}(\mu, z)$, by the transition equation of these two moments (average wage and total number of matches). The transition of the total number of matches (N) is simply given by Equation (6):

$$N' = (1 - \delta)N + p(\theta)(1 - N). \tag{A.1}$$

The transition equation for the aggregate wage is assumed to be a log-linear in the current period's aggregate wage and aggregate productivity (z) as in Krusell and Smith (1998):

$$\log \Omega' = b_1 + b_2 \log \Omega + b_3 \log z. \tag{A.2}$$

We employ an iterative algorithm on a discrete state space as follows:

1. Guess the coefficients for the transition equation for Ω: b_1^0, b_2^0 and b_3^0 in (A.2).

2. Guess the values for θ^0 at each combination of (z, Ω, N).

3. Given the guesses for the transition equations and the value of labor market tightness, θ, solve the Nash bargaining problems for effort choice and wage between a worker and a firm in two steps. In the first step, we solve for the optimal effort. In the common effort model, the effort level chosen by Equation (16). In the individual effort model, each match (cohort) chooses the effort given the wage for that match (cohort) based

on (14). The second step solves the wage for the new matches, based on (12), that persists for T periods given the effort chosen in the first step.

4. Compute the value functions, W_j and J_j for $j = 0, \cdots, T-1$ using Equations (2) and (9).

5. Compute θ^1 using the free entry condition (11). If θ^1 is close enough to θ^0, then move on to the simulation step. Otherwise go back to the step 2.

6. Simulate the decision rules for effort choice and wage for the new matches for a long period (for example 3,000 quarters) to obtain a time series of the numerical distribution of matches and compute a time series of the aggregate variables of interest from the distribution.

7. Obtain the new coefficients for the transition equation for Ω, b_1^1, b_2^1 and b_3^1, through a regression of the simulated aggregate variables. If the new coefficients are close enough to the old ones, then stop. Otherwise go back to step 1.

The following subsections describes steps 3 and 4 in more detail for, respectively, the common-effort and the individual-effort models.

A.1. Common Effort Case

Nash Bargaining for the Common Effort The first step of solving the Nash bargaining problem is to solve the common effort for all matches from (17) of the text, where the value functions are:

$$W(z, \Omega, N) = \Omega - b + \psi \frac{(1-e)^{1-\gamma} - 1}{1-\gamma} + \beta\big(1 - \delta - p(\theta)\big)\mathbb{E}\big[W(z', \Omega', N')|z\big], \qquad \text{(A.3)}$$

and

$$J(z, \Omega, N) = \alpha z \left(\frac{\bar{K}}{N \cdot E}\right)^{1-\alpha} e - \Omega + \beta(1-\delta)\mathbb{E}\big[J(z', \Omega', N')|z\big], \qquad \text{(A.4)}$$

Both W and J are subject to (A.2) and (A.1). E denotes aggregate efficiency; since all matches choose the same effort, aggregate efficiency must equal the common-effort choice, i.e., $E = e(z, \Omega, N)$. We solve the value functions through iterations, explicitly imposing the equilibrium condition for all (z, Ω, N) as follows.

1. Guess initial value functions on discrete grids of states: $W^0(z, \Omega, N)$ and $J^0(z, \Omega, N)$.

2. Solve the Nash bargain for the common effort and update the value functions.

   (a) Guess an equilibrium aggregate efficiency E^0 at each combination of states (z, Ω, N).

   (b) Solve the common effort given the guess E^0: $e^1(z, \Omega, N; E^0)$

   $$\hat{J}^1(z, \Omega, N; E^0)\psi(1-e^1)^{-\gamma} = \hat{W}^1(z, \Omega, N; E^0)\alpha z \left(\frac{\bar{K}}{N \cdot E^0}\right)^{1-\alpha},$$

   where $\hat{W}^1(z, \Omega, N; E^0)$ and $\hat{J}^1(z, \Omega, N; E^0)$ are computed using (A.3) and (A.4), respectively, with E^0, e^1, and W^0 on the right hand sides.

   (c) If $E^0 = e^1$, then compute the new value functions: $W^1(z, \Omega, N) = \hat{W}^1(z, \Omega, N; E^0)$ and $J^1(z, \Omega, N) = \hat{J}^1(z, \Omega, N; E^0)$. Otherwise, go back to the step (a) and try another value for E^0.

3. If W^0 and J^0 are close enough to W^1 and J^1 then move to the second step of the Nash bargaining: the wage for new matches. Otherwise, update the guesses for the value functions and go back to step 1.

Nash Bargaining for the Wage for New Matches The second steop is to solve for the wage for new matches from the first-order condition (13):

$$J_0(w^*; z, \Omega, N) = \big(W_0(w^*; z, \Omega, N) - U(z, \Omega, N)\big),$$

where the approximated value functions $J_0(z, \Omega, N)$ and $W_0(z, \Omega, N)$ are obtained by backwardly iterating equations (2), (7), (9) and (10).

Simulation Once we obtain the solutions for the common effort and the wage for new matches, we simulate these solutions to generate a long series of distributions of matches and, in turn, a series of aggregate variables. Details are as follows.

1. Generate a series of aggregate productivity shocks of length 3,500: $\{z_t\}$ for $t = 1, \cdots, 3500$.

2. Each period of the simulation, compute N_j for $j = 0, \cdots, T-1$ using the transition equation (6), and then $N = \sum_{j=0}^{T-1} N_j$.

3. The aggregate wage (Ω) and the wage for new matches (w_0) are jointly determined to be consistent with wages for other cohorts that were determined j periods earlier.

   (a) Guess an Ω^0.

   (b) Compute the wage for new matches given the guess as $w_0 = w^*(z, \Omega^0, N)$.

   (c) Compute the aggregate wage: $\Omega^1 = \sum_{j=0}^{T-1} \left(\frac{N_j}{N}\right) w_j$.

   (d) If Ω^1 is close enough to Ω^0, then Ω for the period is found. Otherwise, go back to step (a).

4. All aggregate and cohort specific variables can be computed given the state variables computed above.

Equilibrium Transition Equation The equilibrium transition equation for the aggregate wage (Ω) in (A.2) with the benchmark parameters is as follows:

$$\log \Omega' = -0.03549 + 0.90895 \log \Omega + 0.1137 \log z, \qquad R^2 = 0.9992$$

A.2. Individual Effort Case

Nash Bargaining for Individual Effort In this model each cohort's optimal effort is chosen separately given the aggregate efficiency E. Unlike the common-effort case, we cannot impose the labor market equilibrium condition, $E = \sum_{j=0}^{T-1} \left(\frac{N_j}{N}\right) e_j$, at the stage of approximating value functions. This consistency will be established during the simulation. In order to compute the value functions, we employ an algorithm similar to Krusell and Smith (1997). The aggregate efficiency is predicted by a function of state variables at the beginning of the computation:

$$\log E = d_1 + d_2 \log \Omega + d_3 \log z. \tag{A.5}$$

Given the guess for the coefficients, d_i^0 for $i = 1, 2, 3$ and a guess for E, each cohort's effort, $e_j^*(w_j, z, \Omega, N; E)$, is solved from the approximated first order condition as in (14):

$$\hat{J}_j(w_j, z, \Omega, N; E)\psi(1 - e_j)^{-\gamma} = \widehat{(W - U)}_j(w_j, z, \Omega, N; E)\alpha z \left(\frac{\bar{K}}{N \cdot E}\right)^{1-\alpha},$$

where

$$\widehat{(W-U)}_j(w_j, z, \Omega, N; E) = w_j - b + \psi\frac{(1-e_j)^{1-\gamma}-1}{1-\gamma}$$
$$+ \beta(1-\delta)\mathbb{E}\big[(W-U)_{j+1}(w_j, z', \Omega', N')|z\big] - \beta p(\theta)\mathbb{E}\big[(W-U)_0(w^*, z', \Omega', N')|z\big]$$

and

$$\hat{J}_j(w_j, z, \Omega, N; E) = \alpha z \left(\frac{\bar{K}}{N \cdot E}\right)^{1-\alpha} e_j - w_j + \beta(1-\delta)\mathbb{E}\big[J_{j+1}(w_j, z', \Omega', N')|z\big].$$

The value functions W_j and J_j are computed as

$$W_j(w_j, z, \Omega, N) - U(z, \Omega, N) = \widehat{(W-U)}_j\big(w_j, z, \Omega, N; E(z, \Omega)\big)$$

and

$$J_j(w_j, z, \Omega, N) = \hat{J}_j\big(w_j, z, \Omega, N; E(z, \Omega)\big).$$

Nash Bargaining for Individual Effort The step for solving the wage for new matches is essentially the same as that of the common effort case.

Simulation The procedure to simulate the distribution of matches and other aggregate variables are identical to that of the common effort case with one exception. In addition that the wage for new matches be consistent with the aggregate wage (Ω) reflecting other cohorts' wages, the optimal effort for each cohort (e_j^*) should be consistent with aggregate efficiency (E). Details are as follows.

1. Guess an E^0.
2. Compute $e_j^*(w_j, z, \Omega, N; E^0)$ for $j = 0, \cdots, T-1$.
3. Compute the aggregate efficiency: $E^1 = \sum_{j=0}^{T-1}\left(\frac{N_j}{N}\right)e_j^*$.
4. If E^1 is close enough to E^0, then E and e_j^* for the period are found. Otherwise, go back to the step (a).

Equilibrium Prediction Functions The equilibrium prediction functions for the aggregate wage (Ω) in (A.2) and the aggregate efficiency (E) in (A.5) with the benchmark parameters is as follows:

$$\log \Omega' = -0.22532 + 0.42015 \log \Omega + 0.72573 \log z, \qquad R^2 = 0.9735$$

and

$$\log E = -0.20816 + 1.24797 \log \Omega - 0.93171 \log z, \qquad R^2 = 0.9990$$

B. Data Description

B.1. KLEMS Industry Data

The U.S. KLEMS (http://www.bls.gov/mfp/) data provide nominal and real values for gross output, inputs of intermediates, labor, and capital annually from 1987 to 2010 for 60 industries. (See Table 2.) 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, notably Education Services, are reduced compared to national income accounts. The KLEMS data provide 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. We 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. Taken together, the adjustments for capital utilization and worker composition make TFP on slightly less procyclical and wage rates modestly more procyclical. But the adjustments do not affect the estimates of interest, that is, how industry wage flexibility affects cyclicality of TFP, hours, and wages.

B.2. SIPP Data for Measuring Wage Flexibility

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.

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 imputed, 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.

Employed respondents report monthly earnings. In addition, just over half of those employed 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.

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 calculating 4-month and 8-month frequencies of wage changes for stayers it equals 490,604 persons; of these, 408,242 are mapped to one of our 60 KLEMS industries.

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
$\psi = 0.6826$	Scale parameter for utility from leisure
$b = 0.142$	Unemployment insurance benefits
$\kappa = 0.05782$	Vacancy posting cost

Table 2: KLEMS Industries

INDUSTRY	NAICS Code	VA Share	Calvo Frequency
Crop and Animal Production	111,112	1.6	0.27
Forestry and Fishing	113-115	0.4	0.31
Oil and Gas Extraction	211	1.1	0.30
Mining, except Oil and Gas	212	0.4	0.18
Support Activities for Mining	213	0.3	0.18
Utilities	22	2.7	0.31
Construction	23	6.2	0.28
Food, Beverage, and Tobacco	311,312	2.16	0.37
Textile Mills and Textile Products	313,314	0.4	0.27
Apparel and Leather products	315,316	0.4	0.27
Wood products	321	0.4	0.40
Paper Products	322	0.9	0.39
Printing and Related Activities	323	0.6	0.30
Petroleum and Coal products	324	0.9	0.40
Chemical products	325	2.4	0.35
Plastics and Rubber products	326	0.9	0.33
Nonmetallic Mineral Products	327	0.	0.34
Primary Metals	331	0.7	0.28
Fabricated Metal products	332	1.6	0.36
Machinery	333	1.6	0.30
Computer and Electronic products	334	2.2	0.36
Electrical Equipment and Appliances	335	0.7	0.35
Transportation Equipment	336	2.5	0.33
Furniture and related products	337	0.4	0.38
Miscellaneous Manufacturing	339	0.8	0.36
Wholesale Trade	42	6.7	0.31
Retail Trade	44,45	8.0	0.32
Air Transportation	481	0.5	0.32
Rail Transportation	482	0.4	0.30

Water Transportation	483	0.1	0.19
Truck Transportation	484	1.3	0.29
Transit and Ground Passenger Transportation	485	0.2	0.28
Pipeline Transportation	486	0.1	0.28
Other Transportation	487,488,492	1.0	0.38
Warehousing and Storage	493	0.4	0.31
Publishing Industries	511,516	1.4	0.30
Motion Picture and Recording Industries	512	0.5	0.25
Broadcasting and Telecommunications	515,517	3.1	0.35
Information and Data Processing Services	518,519	0.6	0.35
Credit Intermediation and Related Activities	521,522	3.7	0.31
Securities, Commodities, and Investments	523	2.1	0.24
Insurance Carriers and Related Activities	524	2.7	0.31
Funds, Trusts, and other Financial Vehicles	525	0.9	0.24
Real Estate	531	4.9	0.31
Rental and Leasing Services	532,533	1.7	0.24
Legal Services	5411	1.9	0.29
Miscellaneous Professional, Scientific and Technical Services	5412-5414,5416-5419	5.6	0.32
Computer System Design and Services	5415	1.2	0.32
Management of Companies and Enterprises	55	2.3	0.32
Administrative and Support Services	561	3.2	0.32
Waste Management and Remediation Services	562	0.4	0.31
Educational Services	61	0.2	0.38
Ambulatory Health Care Services	621	3.9	0.30
Hospitals, Nursing, Residential Care Facilities	622,623	1.4	0.37
Social Assistance	624	0.3	0.38
Performing Arts, Spectator Sports, Museums, and Related Activities	711,712	0.4	0.36
Amusements, Gambling, and Recreation	713	0.5	0.30
Accommodation	721	0.9	0.32
Food Services and Drinking Places	722	2.0	0.31
Other Services, except Government	81	2.6	0.29

Table 3: Industry Wage and TFP Fluctuations

	Dependent Variable			
	TFP for Value Added		TFP for Gross Output	
Wage	0.54 (0.14)	−0.07 (0.24)	0.28 (0.07)	−0.04 (0.09)
Wage*Labor's Share		1.12 (0.30)		1.12 (0.19)

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. Regressions include a full set of year dummies. Industry observations are weighted by its relative value added. Standard errors (in parentheses) are clustered within industries and within years.

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
1990-1993 Panels (Approx. 1990-1995)	0.69	0.78	0.33	0.30	0.23
1996 Panel (Approx. 1996-1999)	0.74	0.83	0.34	0.38	0.28
2001 Panel (Approx. 2001-2004)	0.74	0.82	0.37	0.33	0.25
2004 Panel (Approx. 2004-2007)	0.37	0.54	0.06	0.27	0.21
2008 Panel (Approx. 2008-2011)	0.27	0.38	0.04	0.18	0.15
Average 1990 to 2001 Panels	0.71	0.81	0.35	0.33	0.25
Average over all Panels	0.56	0.68	0.24	0.29	0.23

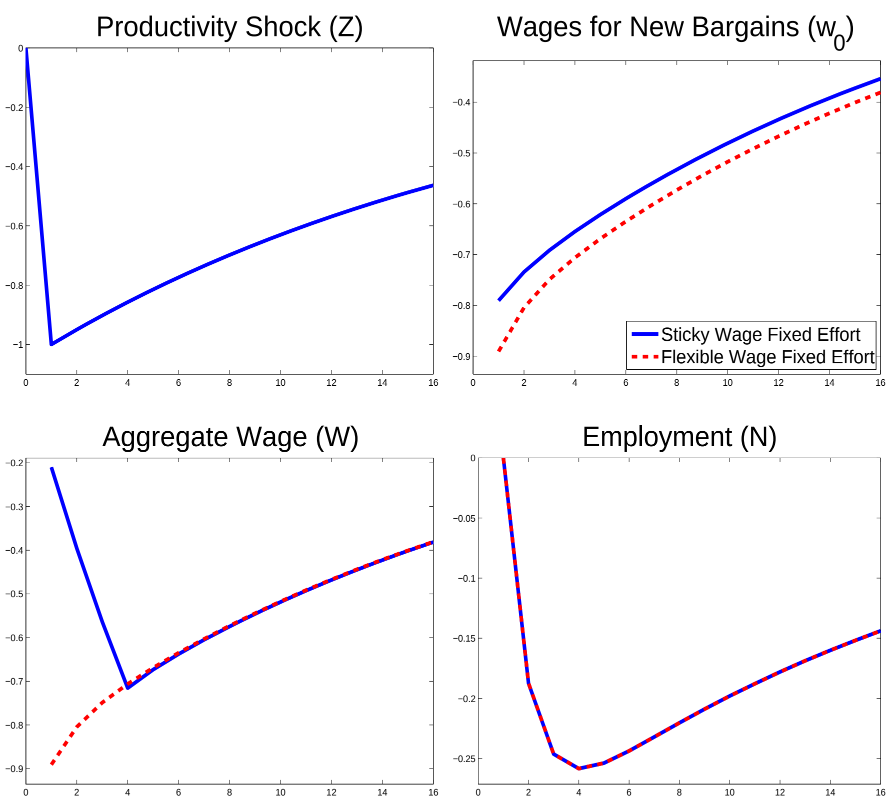
Notes: Observation by panel (top to bottom) are 218,819, 86,086, 46,894, 70,614, 68,191, 351,799, and 490,604. Observations are weighted both by the SIPP sampling weight and by the workers relative monthly earnings.

Table 5: Industry Cyclicality by Wage Stickiness

	Dependent Variable		
	Hours	TFP	Wage
	All 60 Industries		
GDP*Stickiness	0.08 (.06)	−0.14 (.09)	0.14 (.07)
	24 Goods Industries		
GDP*Stickiness	0.16 (.10)	−0.41 (.14)	0.03 (.08)
	12 Goods Industries With Lower Labor Share		
GDP*Stickiness	0.12 (.07)	−0.25 (.08)	0.10 (.08)
	12 Goods Industries With Higher Labor Share		
GDP*Stickiness	0.09 (.10)	−0.98 (.33)	−0.16 (.15)
	14 Durable Goods Industries		
GDP*Stickiness	0.13 (.08)	−0.82 (.26)	−0.13 (.14)

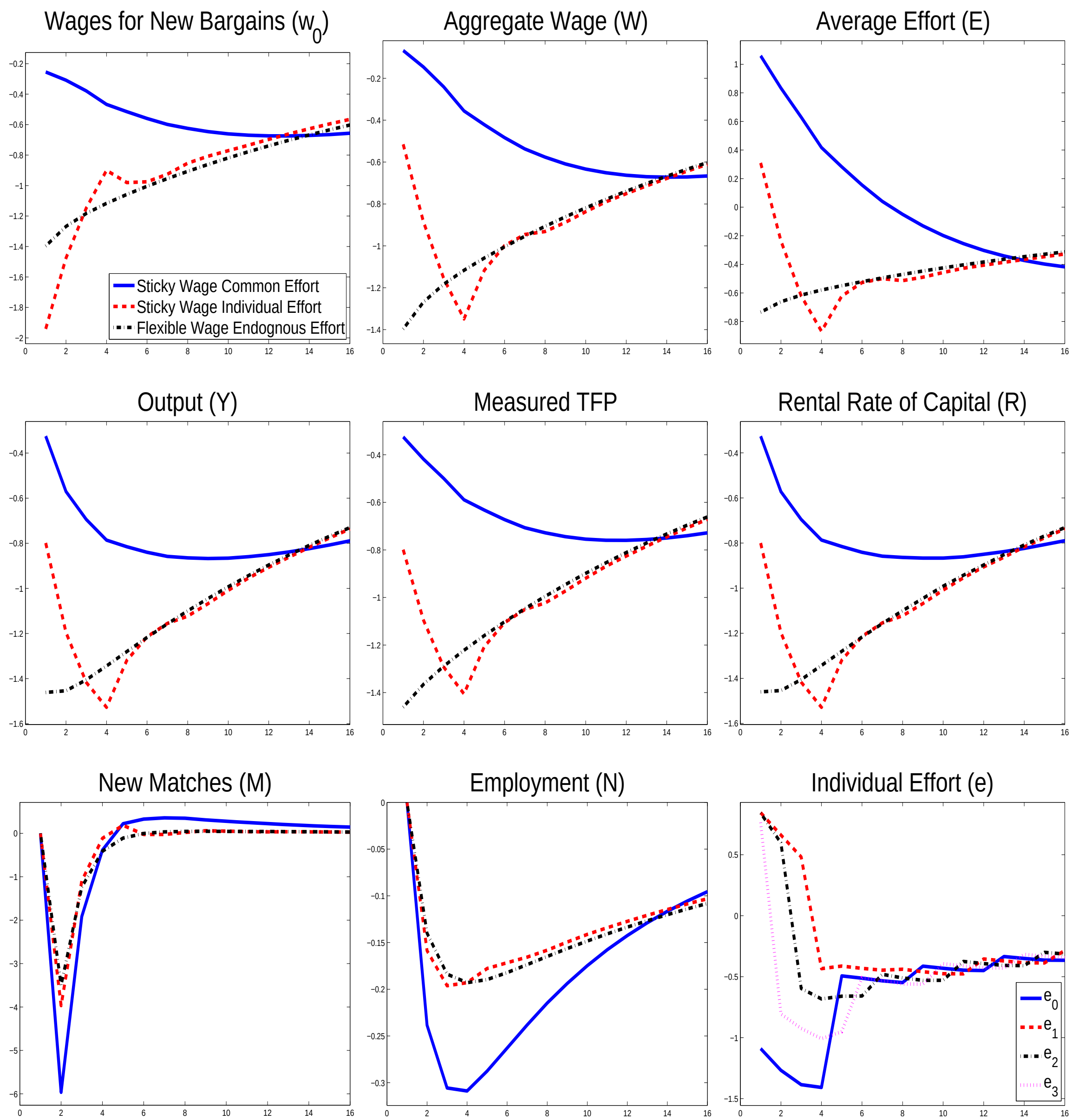
Notes: GDP is HP-filtered aggregate real GDP. Stickiness is the Calvo implied duration of wages in the industry (in months). TFP measures are adjusted for estimated capital utilization. TFP and real wage adjusted for compositional changes. Regressions include a full set of year dummies. Industry observations are weighted by its relative value added. Standard errors (in parentheses) are clustered within industries and within years.

Figure 1: Model with Fixed Effort



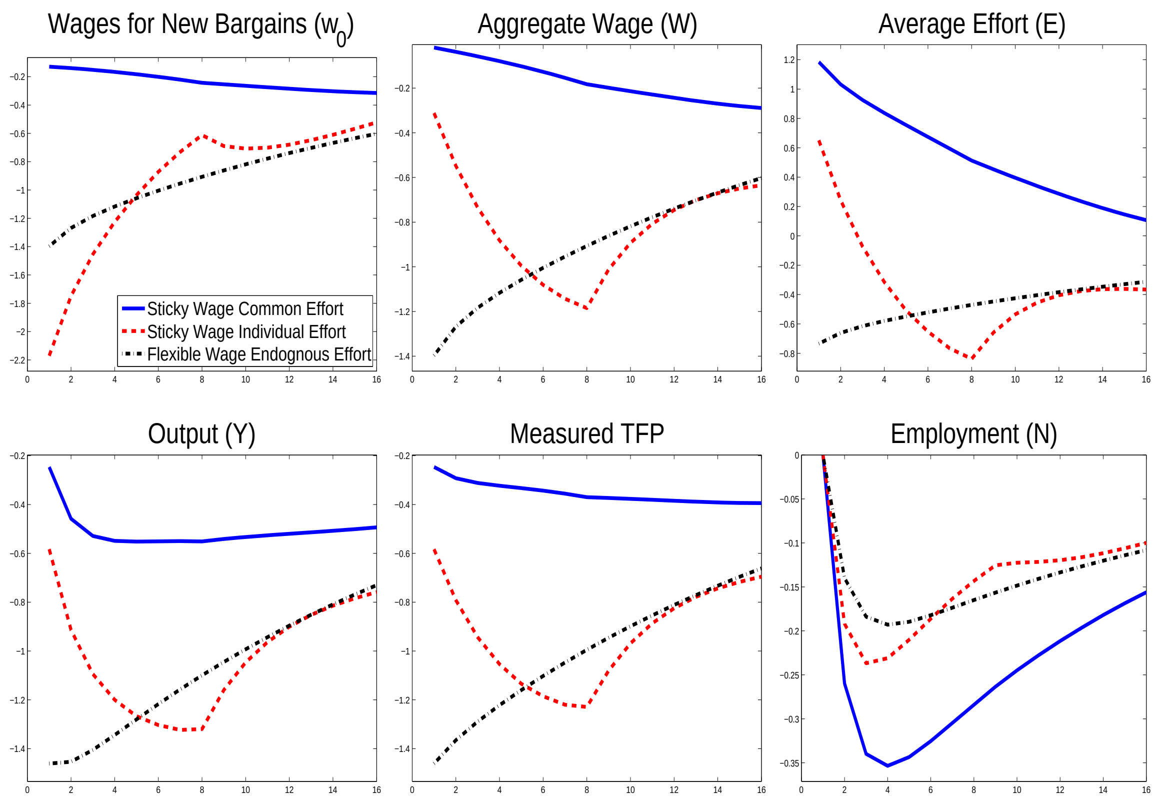
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dashed line (−−) represents the model with flexible wages. The solid line represents the model with sticky wages. The x axis represents periods (in quarters) and y axis represents percentage deviation from the steady state.

Figure 2: Model with Variable Effort



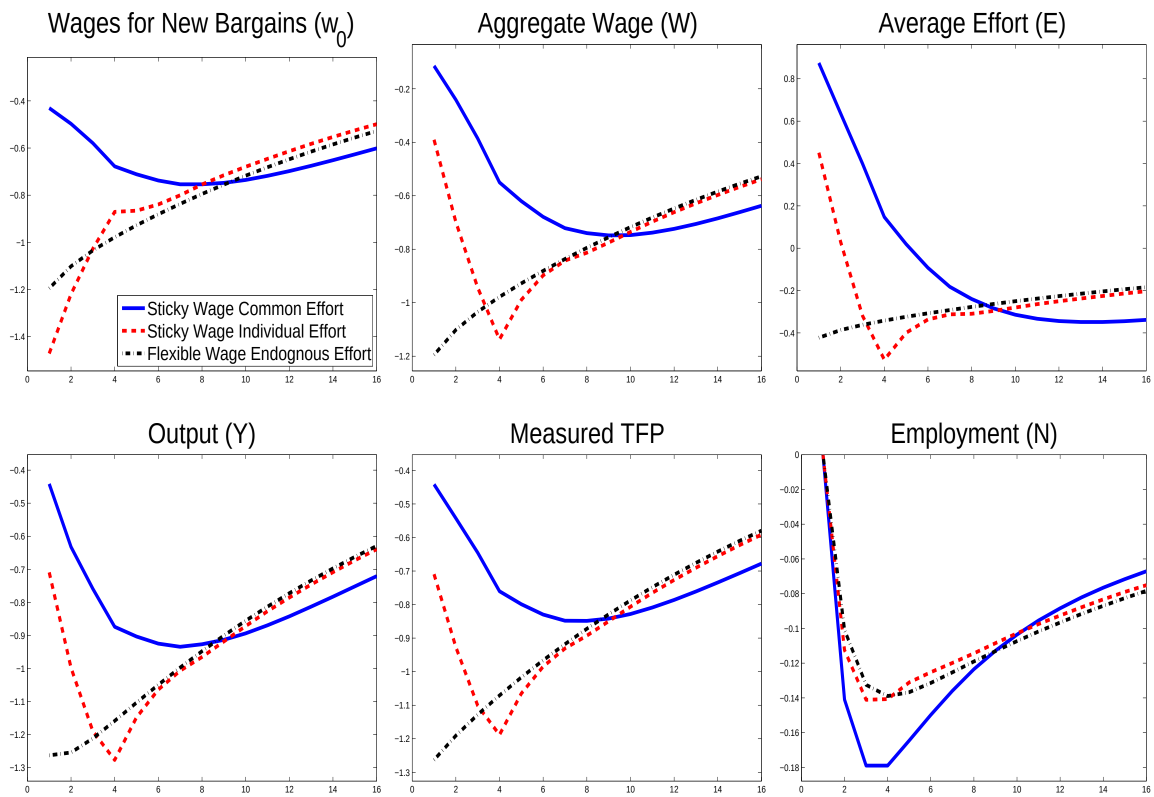
Notes: Productivity decreases by 1% in period 1 autocorrelation of 0.95. The dash-dot line (−.) represents the model with flexible wages. The dashed line (−−) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice. All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

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



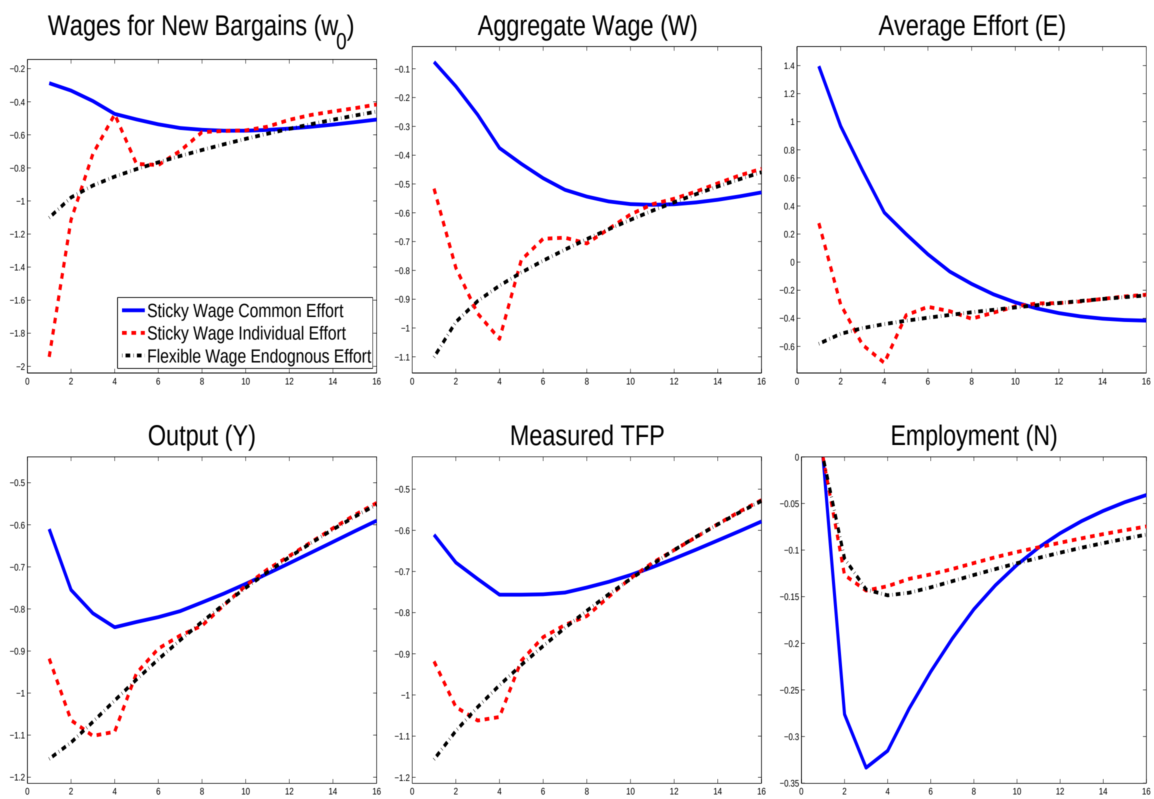
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dash-dot line (−.) represents the model with flexible wages. The dashed line (−−) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice.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

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



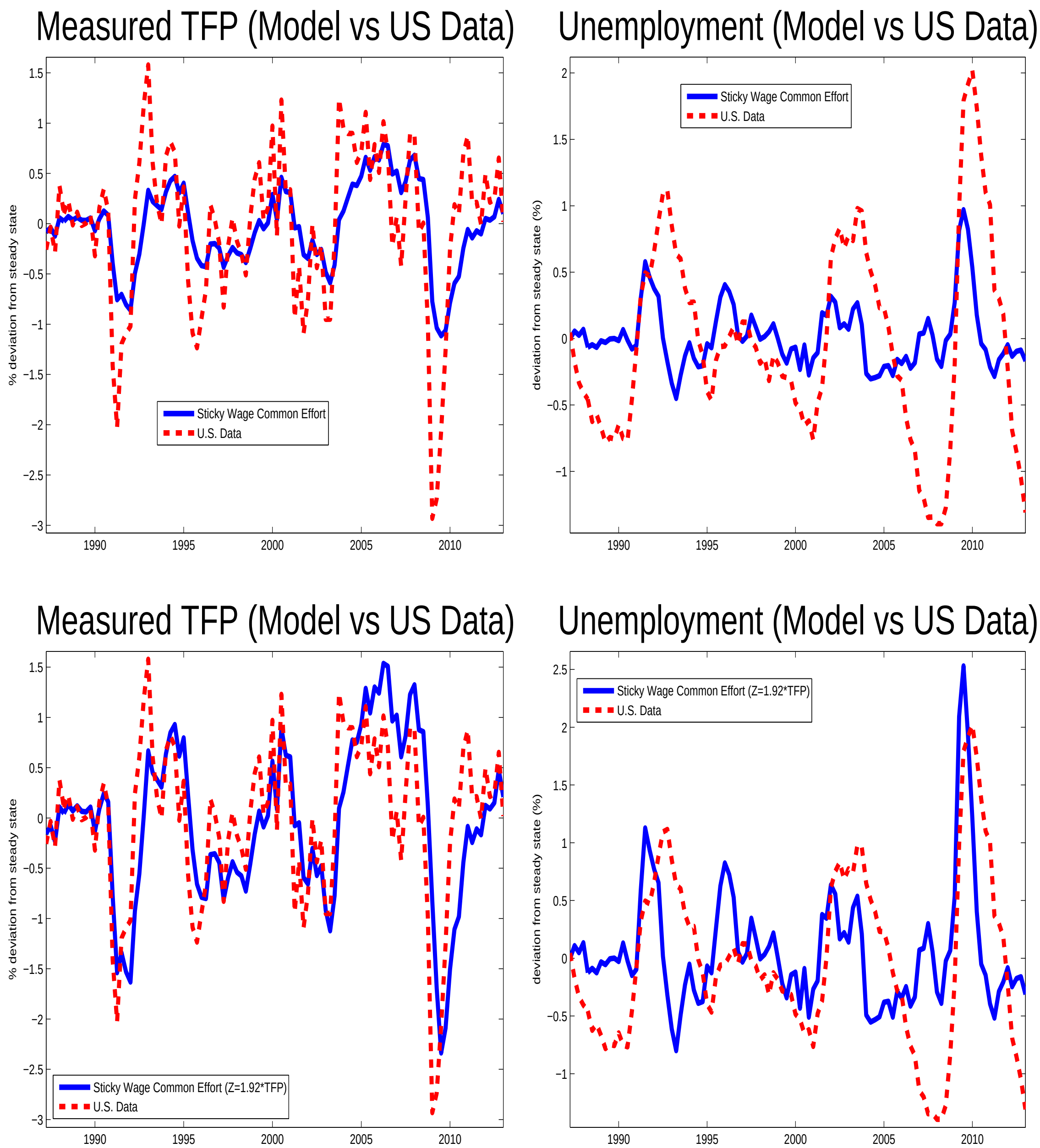
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dash-dot line (–.) represents the model with flexible wages. The dashed line (−−) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice.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

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



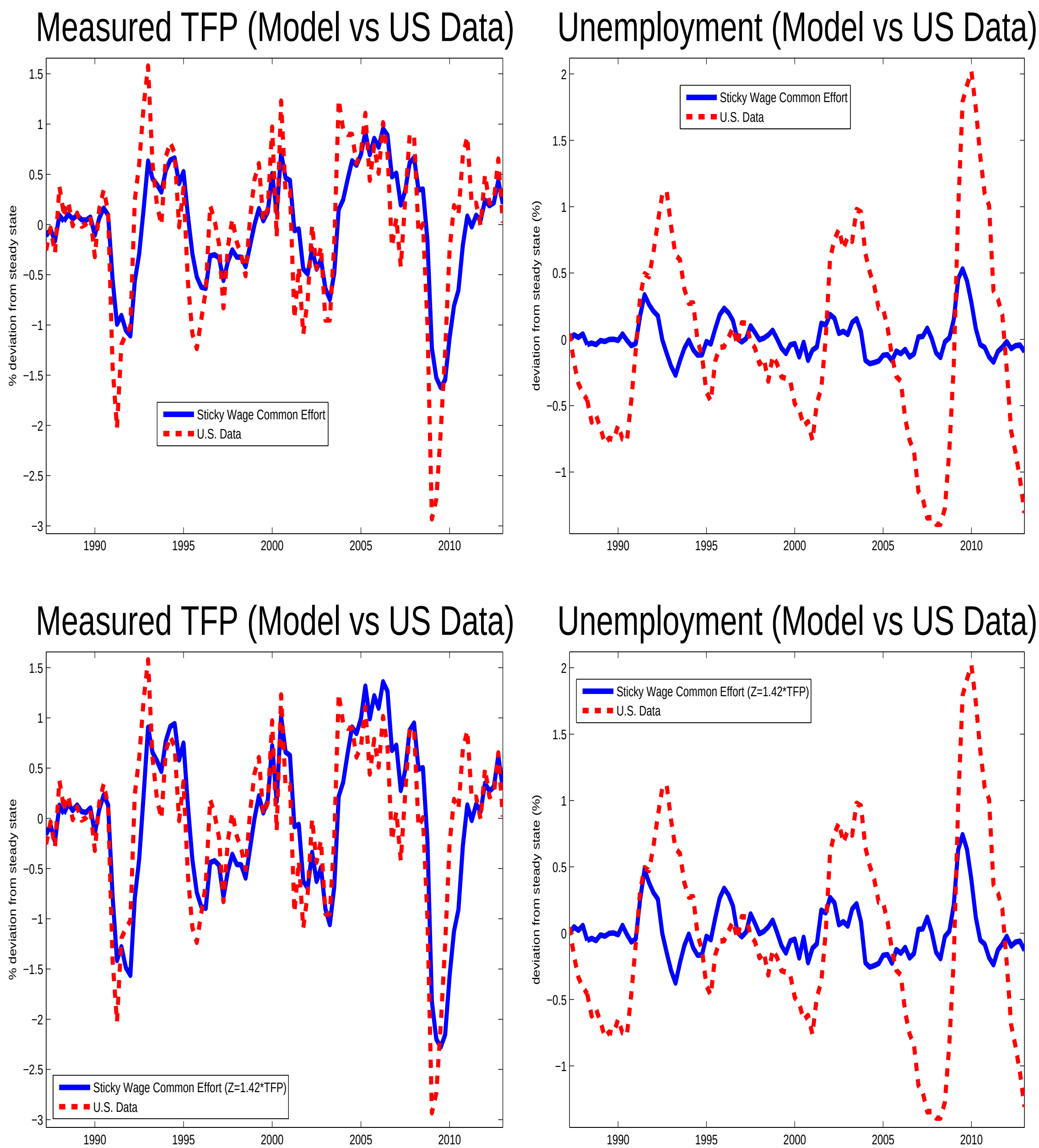
Notes: Productivity decreases by 1% in period 1 with autocorrelation of 0.95. The dash-dot line (−.) represents the model with flexible wages. The dashed line (−−) represents the sticky wage model with individual effort choice. The solid line represents the sticky wage model with common effort choice. 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 1.92 (i.e., $z_t = 1.92 \times TFP_t^{US}$).

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



Notes: In the upper panel, we use the actual time series of (detrened) 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.