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The Cyclical Behavior of Labor Force Participation*

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Abstract

We document that labor force participation declines in the short run following a positive technology shock. The countercyclical response of labor force participation to a technology shock contrasts with the well documented mild procyclical behavior of labor force participation in the business cycle. In a search model of the labor market that incorporates a participation choice, we show that a positive technology shock reduces labor force participation in the short run under a reasonable calibration. In the calibrated model, discount factor shocks induce a procyclical response of labor force participation. As a result, the model can generate both the countercyclical response to technology shocks and the procyclical behavior, consistent with the evidence. Our results indicate an important role of nontechnology shocks for explaining labor market fluctuations.

Keywords: Labor force participation; Unemployment; Technology shocks; Discount factor shocks

JEL Classification: E24, E32, J22, J64

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1 Introduction

A large body of business cycle research has studied the cyclical fluctuations of unemployment, but most studies assume that the labor force is constant.[1] This is perhaps not surprising, as fluctuations in labor force participation are small compared with unemployment fluctuations in the U.S. data. However, understanding the cyclical behavior of labor force participation can provide insight into the nature of unemployment fluctuations. For instance, the decline in labor force participation during the Great Recession and its aftermath stirred up debate about the severity of the labor market slump and whether the unemployment rate is an accurate measure of it.[2]

This paper makes two contributions. First, we examine the empirical response of labor force participation to a technology shock using a structural vector autoregression (VAR), and document that a positive shock reduces labor force participation in the short run. To the best of our knowledge, our paper is the first to document the empirical response of labor force participation to a technology shock. Based on simulated data from the VAR, the correlation of labor force participation and output conditional on technology shocks is -0.91. The highly countercyclical response of labor force participation to a technology shock stands in contrast with the well documented mild procyclical behavior of labor force participation in the business cycle. Indeed, the unconditional correlation of labor force participation and output in the postwar U.S. data is 0.17. The large difference between the two correlations implies that technology shocks are not a major driver of fluctuations in labor force participation.

The new evidence also points to an important role of nontechnology shocks for explaining fluctuations in unemployment. The unemployment rate might overstate or understate the

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[1]Rogerson and Shimer (2010) review the macro-labor literature that examines the implications of labor market search frictions for business cycle fluctuations.

[2]For analyses of the Great Recession's effect on labor force participation, see Aaronson et al. (2014), Erceg and Levin (2014), and Van Zandweghe (2012).

depth of recessions, in terms of employment losses, depending on the mix of shocks causing the recession. In a technology-driven recession, a rise in labor force participation would dampen the decline in employment, so the rise in unemployment would overstate the depth of the recession (although the productivity decline would worsen output losses). But if the recession is caused by a demand shock, a decline in labor force participation would exacerbate the decline in employment. Therefore, the rise in unemployment would understate the severity of the recession.[3] A large body of research has analyzed various propagation mechanisms that can lead technology shocks to generate the large unemployment fluctuations observed in the data. Prominent amplification mechanisms include wage rigidity (Hall, 2005; Shimer, 2005), an alternative calibration of the standard search model (Hagedorn and Manovskii, 2008), an alternative wage bargaining mechanism (Hall and Milgrom, 2008), fixed matching costs (Pissarides, 2009), and on-the-job search (Krause and Lubik, 2006; Menzio and Shi, 2011). Our empirical evidence indicates that in addition to propagation mechanisms, the nature of shocks is an important factor for explaining unemployment fluctuations.

The paper's second contribution is to provide an economic explanation for the evidence. We show that two straightforward extensions of the standard search model can account for the two facts—that is, the mild procyclical behavior of labor force participation and its countercyclical response to technology shocks. The first extension consists of incorporating a participation choice of households, whose leisure is diminished not only by the utility cost of employment but also by the utility cost of searching for jobs. Shimer (2013) shows that the assumption of wage rigidity in such a model amplifies unemployment fluctuations and allows the disutility of employment and search to be determined independently. We calibrate the

[3]Labor force participation and unemployment may have different drivers over the business cycle. For example, fluctuations in labor force participation may arise largely from shocks affecting labor supply whereas fluctuations in unemployment may be largely due to technology shocks affecting labor demand. Even so, nontechnology shocks would affect unemployment dynamics through the effect of labor force participation on unemployment. Elsby, Hobijn, and Sahin (2015) examine gross worker flows and find that changes in labor force participation account for around one third of unemployment fluctuations.

ratio of the two disutility parameters to generate a decline in labor force participation after a positive technology shock, the magnitude of which corresponds with our VAR evidence. The second extension is adding discount factor shocks. The empirical finance literature has established that discount rates vary over time (e.g. Cochrane, 2011), and we assume a portion of this variation is exogenous to labor market fluctuations. Under our model calibration, an expansionary discount factor shock increases labor force participation and employment, while reducing unemployment. Moreover, discount factor shocks induce a larger response of labor force participation in absolute value than technology shocks in the model. As a result, the model with two shocks can generate procyclical labor force participation along with the countercyclical response to technology shocks.

The conclusion that nontechnology shocks are an important driver of labor market fluctuations is consistent with previous research. In a search model, Hall (2017) examines implications of large discount factor volatility, as inferred from the stock market, for unemployment fluctuations and shows that the discount factor movements can account for a substantial portion of observed unemployment fluctuations. Mortensen and Nagypal (2007) highlight a role for job separation shocks to account for the volatility of unemployment. Furthermore, the empirical business cycle literature views nontechnology shocks as nontrivial drivers of cyclical fluctuations.[4] Different from the previous studies, our paper provides evidence favoring an important role for nontechnology shocks in explaining labor market fluctuations based on the dynamics of labor force participation.

A small number of research papers has studied the cyclical properties of labor force participation. Tripier (2003) and Veracierto (2008) show that real business cycle models with unemployment and labor force participation predict a procyclical or acyclical unemployment

[4]In a benchmark estimated medium-scale DSGE model, Smets and Wouters (2007) attribute no more than one third of the forecast error variance of output to neutral technology shocks. Adding labor market search in an estimated DSGE model, Gertler, Sala, and Trigari (2008) find a similar contribution of neutral technology shocks to the forecast error variance of output growth.

rate. Shimer (2013) shows that in such a model, wage rigidity can render the unemployment rate countercylical, consistent with the U.S. data, and Tüzemen (2017) shows that allowing on-the-job search can similarly generate a countercyclical unemployment rate. However, these previous studies evaluate model predictions for labor market dynamics based on technology shocks against unconditional correlations of labor force participation and unemployment.[5]

Our paper is also related to the VAR literature on the response of hours worked to a technology shock. Using long-run restrictions to identify technology shocks, Galí (1999) showed that hours decline after a positive shock, spawning a extensive literature. We find that labor force participation declines after a positive technology shock, regardless of whether we use short-run or long-run identifying restrictions. The short-run restrictions lead unemployment to decline more than the rise in employment, so labor force participation declines. The long-run restrictions lead employment to decline more than the rise in unemployment, so participation again declines. Our conclusion that technology shocks cannot be a major source of business cycle fluctuations is similar to that of Galí (1999); however, our argument is based on the response of labor force participation to a technology shock and does not depend on whether such shocks are identified based on short-run or long-run restrictions.

The remainder of the paper proceeds as follows. Section 2 presents new evidence on the dynamic behavior of labor force participation. Section 3 describes a business cycle model with search frictions, and Section 4 provides a quantitative evaluation of the model. Section 5 examines the robustness of the new evidence under a different identification scheme for technology shocks. Section 6 concludes.

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[5]A recent exception is Krusell et al. (2017), who build a heterogeneous-agent model with search frictions and aggregate shocks to the employment arrival and separation rates to explain the cyclical properties of gross worker flows between employment, unemployment and inactivity. Campolmi and Gnocchi (2016) and Nucci and Riggi (2018) examine implications of endogenous labor force participation in DSGE models with labor market search frictions and multiple shocks. The presence of nominal price rigidity and a monetary policy rule in their models affects the propagation of shocks.

2 Empirical Evidence

This section presents new evidence about the response of labor force participation to a technology shock. Estimating a structural VAR reveals that labor force participation declines temporarily after a positive technology shock. The negative response is at odds with the stylized fact that labor force participation is procyclical.

2.1 Dynamic responses to a technology shock

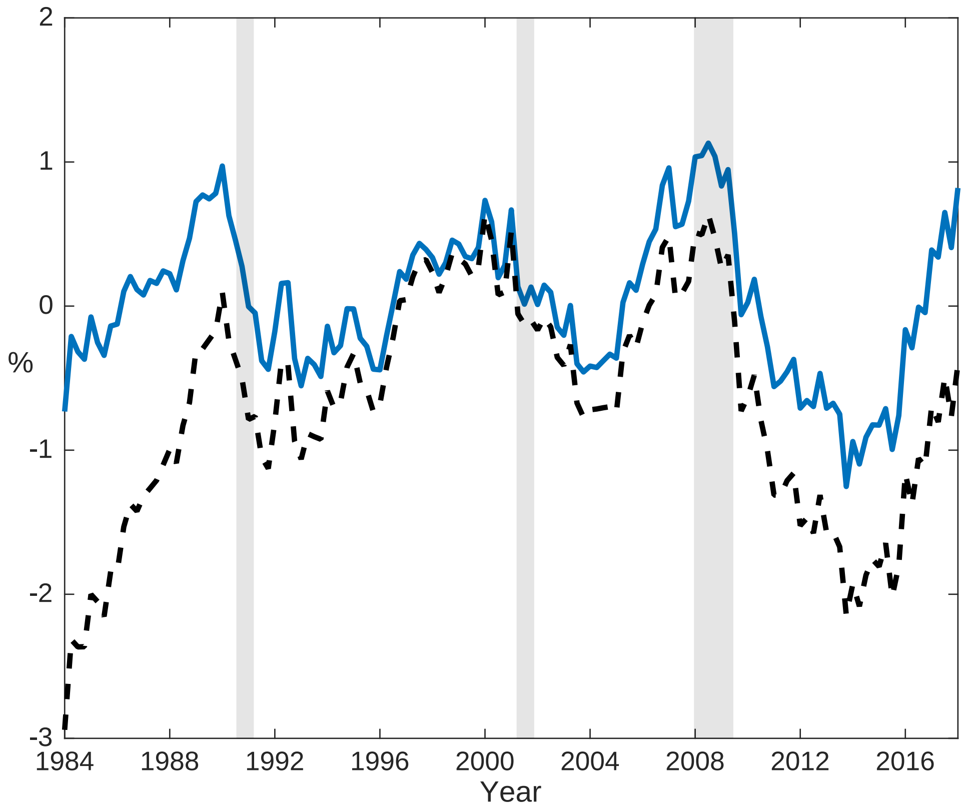
The empirical analysis uses quarterly U.S. data for productivity, labor force participation, the unemployment rate, and employment.[6] Data used in the estimation are in logarithms and detrended prior to estimation using a Hodrick-Prescott (HP) filter with a high value for the smoothing parameter of $\lambda = 10^5$, following Shimer (2005, 2013). The solid line in Figure 1 displays the cyclical component of labor force participation. It exhibits procyclicality: participation declined during and in the aftermath of each of the three recessions since 1984 before rebounding in the expansion. For comparison, the dashed line shows an alternative measure of cyclical labor force participation, which is detrended with the Congressional Budget Office (CBO)'s estimate of the potential labor force participation rate. The CBO carefully accounts for demographic and other trend shifts using a cohort model.[7] While the dashed line lies below the solid line, the correlation between the two series is high (0.78).

To characterize the dynamic response of labor force participation to a technology shock,

[6]Productivity is measured as real GDP divided by civilian employment, 16 years and over; labor force participation is the civilian labor force participation rate, 16 years and over; the unemployment rate is the civilian unemployment rate, 16 years and over; employment is the civilian employment-population ratio, 16 years and over. The sample period is 1952:Q1–2018:Q2.

[7]See Montes (2018) for details about the CBO's methodology, which builds on the methods of Kudlyak (2013) and Aaronson et al. (2014). The CBO's quarterly series covers the period from 1984:Q1 to 2018:1.

Figure 1: The cyclical component of labor force participation.



Notes: The figure shows the deviation of log labor force participation from trend, which is the HP filter (the solid line) or the CBO's estimate of the potential labor force participation rate (the dashed line). The HP filter uses the data series for labor force participation from 1952:Q1 to 2018:Q2 and smoothing parameter $\lambda = 10^5$. Gray bars denote NBER-defined recessions.

we identify a structural shock to labor productivity.[8] Identification of the technology shock follows the method of Fujita and Ramey (2007).[9] Accordingly, technology shocks are recovered based on the identifying assumption that no other shocks affect productivity contemporaneously. In addition to this recursive identification scheme, the exogenous component of productivity is recovered from the structural shocks by setting the coefficients on the lags of other endogenous variables equal to zero in the equation for productivity. Then the impulse responses are generated from a quasi-VAR system that relates each variable to lags of the exogenous component of productivity, lags of the endogenous variables except productivity, and the technology shock.[10]

Figure 2 shows the empirical responses to a one-standard-deviation (positive) technology shock. Labor force participation declines on impact for about 4 quarters, then turns positive (upper right panel). However, while the short-run decline is significantly different from zero, the subsequent rise is not.[11] Fluctuations in labor force participation reflect fluctuations in unemployment and employment. Thus, labor force participation declines as a fall in unemployment outweighs a rise in employment (lower panels). In absolute magnitudes, the response of participation is smallest, the response of the unemployment rate is largest, with an intermediate response of employment. A priori, labor force participation could rise or fall in a boom, depending on whether fewer workers become discouraged and more choose

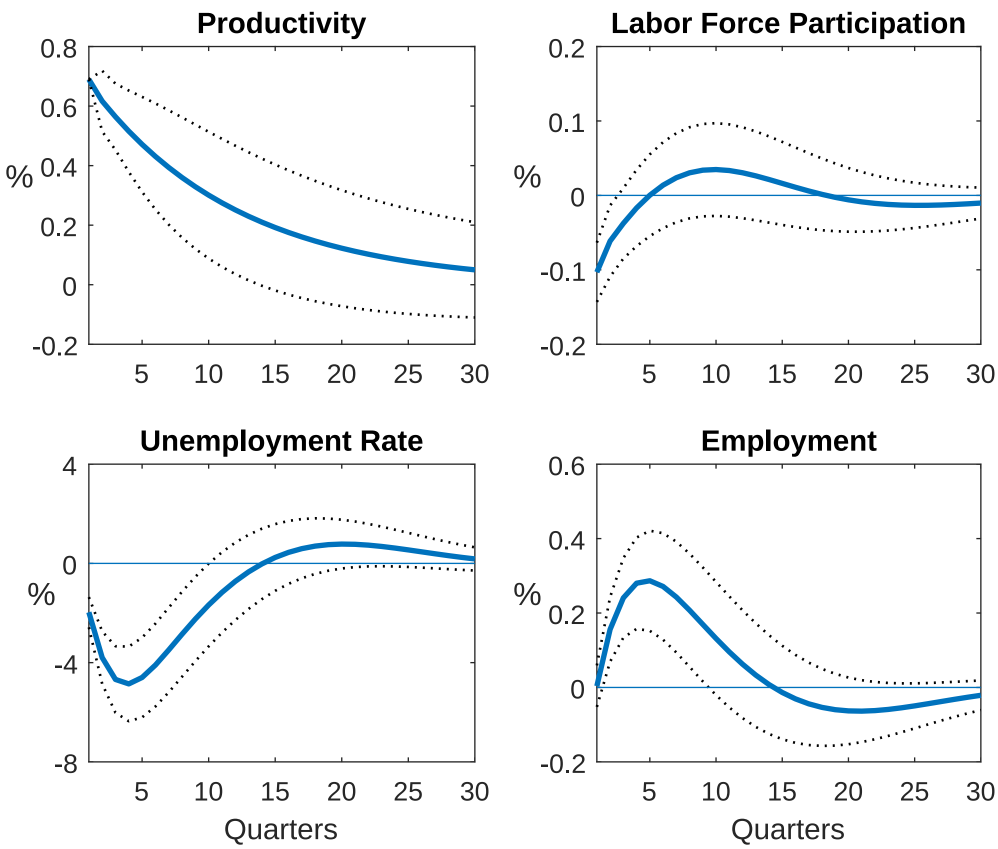
[8]We use the term technology shock as equivalent with total factor productivity shock. It is sometimes also referred to as a neutral technology shock.

[9]Fujita and Ramey (2007) use cubic time polynomials to remove the trend from the time series used in their VAR (productivity, labor market tightness, and employment). The correlation of cyclical labor force participation obtained with their filtering procedure and the CBO's estimate of potential labor force participation is lower (0.19).

[10]The lag length of the VAR is set to two quarters based on the Schwarz criterion. However, the results are similar based on the commonly used lag length of four quarters.

[11]The response of labor force participation is qualitatively unchanged when employment is dropped from the vector of variables. Using prime-age labor force participation (ages 25 to 54) rather than the aggregate in the estimation also produces a significant contractionary response to a technology shock in the short run.

Figure 2: Empirical impulse responses to a technology shock.



Notes: The solid lines are impulse responses obtained by estimating a structural VAR during the period 1952:Q1–2018:Q2 on the logarithms of labor productivity, the unemployment rate, the labor force participation rate, and the employment-population ratio. The lag length of the VAR is two quarters as determined by the Schwarz criterion. Labor productivity is measured as real GDP divided by civilian employment. The technology shock is identified using the method of Fujita and Ramey (2007). The dashed lines are ± 2-standard-deviations confidence intervals obtained from $1,000$ bootstrap replications of the VAR.

to search for a job, or whether more people feel wealthy enough to remain inactive so fewer workers search. The tendency for labor force participation to fall in a boom, and rise in a recession, is known as the "added worker effect," whereas the tendency for it to rise in a boom, and decline in a recession, is known as the "discouragement effect." Thus, Figure 2 implies that the added worker effect of a technology shock dominates the discouragement effect.

2.2 Business cycle statistics

Labor force participation is relatively stable and mildly procyclical. The top panel of Table 1 shows the detrended time series produce these stylized facts. The first line reports the standard deviations of labor force participation, the unemployment rate, and employment relative to that of output. Fluctuations in labor force participation are smaller than those in employment and the unemployment rate. The second line reports correlations with output. With a correlation of 0.17, labor force participation is mildly procyclical, whereas the unemployment rate and employment are strongly countercyclical and procyclical, respectively.[12]

The evidence presented in Figure 2 is inconsistent with the unconditional correlation of output and labor force participation. The third and fourth lines of Table 1 report the standard deviation of output, the relative standard deviations of the labor market variables, and their correlations with output based on simulated data from the VAR conditional on technology shocks. The unconditional and conditional correlations of labor force participation with output are strikingly different. Whereas the unconditional correlation is positive, the

[12] Van Zandweghe (2017) documents a break in the cyclicality of labor force participation around 1984, when the correlation of labor force participation and output more than doubled. The responses to a technology shock shown for the long sample from 1952:1 to 2018:2 are qualitatively unchanged when the VAR is reestimated on the subsamples from 1952:1 to 1983:4 and from 1984:1 to 2018:2, although the magnitude of the responses are smaller in the most recent subsample. Thus, the increase in the cyclicality of labor force participation since 1984 indicates that the economy underwent some structural change or that the relative importance of nontechnology shocks for labor force participation increased.

Table 1: Business cycle statistics for the labor market.

	Variable X	LF	UR	E
1.	Std(X)/Std(Y)	0.238	8.139	0.628
2.	Corr(X,Y)	0.174	-0.869	0.774
3.	Std(X)/Std(Y)	0.148	4.365	0.242
4.	Corr(X,Y)	-0.908	-0.793	0.248

Notes: Lines 1 and 2 report unconditional business cycle statistics of the detrended time series from 1952:1 to 2018:2. Lines 3 and 4 report statistics of simulated data generated by the estimated VAR conditional on technology shocks. The simulated time series contain 50,000 quarters, of which the first 5,000 quarters are discarded. Y, LF, UR, and E denote real GDP per capita, the labor force participation rate, unemployment rate, and the employment-population ratio, respectively.

conditional correlation is strongly negative (-0.91), in line with the impulse responses shown in Figure 2. Therefore, technology shocks alone cannot account for the procyclicality of labor force participation. The relative standard deviations conditional on technology shocks are smaller than the unconditional ones, but the pattern across the three variables is the same: the unemployment rate is the most volatile and labor force participation is the least volatile. Next we assess how well two straightforward extensions of the standard search model, including a labor force participation decision and a discount factor shock, can account for this evidence.

3 A Search Model with Labor Force Participation

The model economy is populated by a representative household and a representative firm. Labor supply is elastic as the household faces a decision between leisure and labor force participation. The labor market is characterized by search frictions and wage rigidity. The model is similar to that proposed by Shimer (2013), except for two differences. First, in addition to a technology shock our model has a discount factor shock, which affects the cyclicality of labor force participation. Second, for simplicity we abstract from capital.

3.1 Representative household

The representative household consists of a large number of family members with identical preferences over consumption and leisure. Each member is infinitely lived, has a subjective discount factor $\beta \in (0, 1)$, and maximizes expected utility. Each period a household member is either employed, unemployed, or inactive, incurring a disutility of $\gamma_n > 0$, $\gamma_u > 0$, or zero, respectively. The household maximizes expected utility

$$E_0 \sum_{t=0}^{\infty} \beta^t e_t^d \left(\ln C_t - \gamma_n N_t - \gamma_u U_t\right).$$

Here E_t is the rational expectations operator, e_t^d is a shock to the discount factor, C_t denotes per-capita consumption, N_t is the employment-population ratio, and U_t is the unemployment-population ratio in period t. The optimization is subject to the household's budget constraint $C_t = W_t N_t$, where W_t is the wage rate, and to the employment accumulation constraint

$$N_{t+1} = (1 - s)N_t + f_t U_t, \tag{1}$$

where $s \in (0, 1)$ is the constant job separation rate and f_t is the job finding rate. Unemployed workers who find a job begin working in the next period. The assumption that family members insure each other against variations in labor income was introduced by Merz (1995) and is common in business cycle models of labor search. The discount factor shock follows a stochastic process

$$\ln e_t^d = \rho_d \ln e_{t-1}^d + \epsilon_t^d, \qquad \epsilon_t^d \sim N(0, \sigma_d^2). \tag{2}$$

Household optimization yields the equilibrium condition for labor force participation:

$$\frac{\gamma_u C_t}{f_t} = \beta E_t \frac{C_t}{C_{t+1}} \frac{e_{t+1}^d}{e_t^d} \left[W_{t+1} - \gamma_n C_{t+1} + (1 - s) \frac{\gamma_u C_{t+1}}{f_{t+1}} \right]. \tag{3}$$

This condition requires that the expected cost of assigning a nonemployed household member to search for a job is equal to the expected benefit. The expected cost is the product of the per-period flow disutility of unemployment, in consumption terms, and the time until a job is found. The expected benefit of job search consists of the present value of the future wage net off the disutility of labor once employed, and the foregone future search cost. The household applies a stochastic discount factor to evaluate today's search cost against tomorrow's benefit.[13]

3.2 Representative firm

The representative firm produces output Y_t using a labor-only technology to maximize the present value of its profits

$$E_0 \sum_{j=0}^{\infty} \beta^j \frac{C_t}{C_{t+j}} \frac{e^d_{t+j}}{e^d_t} \left(Y_t - W_t N_t\right),$$

subject to the production function

$$Y_t = A_t(N_t - V_t) \tag{4}$$

and the firm's employment accumulation constraint

$$N_{t+1} = (1-s)N_t + q_t V_t. \tag{5}$$

Here, V_t is the number of employees allocated to recruiting, so $N_t - V_t$ is the number of workers allocated to production, and q_t is the number of new hires per recruiter, or the recruiter efficiency. The technology level A_t undergoes stochastic shocks along a deterministic trend g, that is $A_t = g^t e^a_t$, where

$$\ln e^a_t = \rho_a \ln e^a_{t-1} + \epsilon^a_t, \qquad \epsilon^a_t \sim N(0, \sigma^2_a). \tag{6}$$

Firm optimization yields the equilibrium condition for recruiting:

$$\frac{A_t}{q_t} = \beta E_t \frac{C_t}{C_{t+1}} \frac{e^d_{t+1}}{e^d_t} \left[A_{t+1} - W_{t+1} + (1-s)\frac{A_{t+1}}{q_{t+1}}\right], \tag{7}$$

[13] While U.S. data show large monthly worker flows from inactivity to employment, the household in the model cannot allocate inactive members directly to employment. We leave this extension of the model for future work.

which balances the expected cost and benefit of recruiting a worker for the firm. The expected cost is the foregone marginal product of labor of a recruiter multiplied by the time needed to fill a vacancy. The expected benefit of recruiting consists of the present value of the future marginal product of the worker net off the wage once a job is filled, and the foregone future recruiting cost. For this intertemporal decision the firm applies the household's stochastic discount factor.

3.3 Labor market and equilibrium

Job searchers and recruiters meet in the labor market according to the matching function

$$M_t = \mu U_t^{\xi} V_t^{1-\xi}, \tag{8}$$

where $\xi \in (0,1)$ is the unemployment elasticity of the matching function and M_t is the number of new worker-job matches. Once an unemployed worker and a recruiter meet they determine the worker's wage, which splits the surplus of the match between the worker and the firm. Following Shimer (2005, 2013) and Hall (2005), we assume that wages are rigid. Specifically, wages, W_t, may adjust partially to a target wage, W_t^*, as follows:

$$W_t = (1-\rho)W_t^* + \rho g W_{t-1}, \tag{9}$$

where $\rho \in [0,1]$ is the degree of wage rigidity. The target wage is the outcome of Nash bargaining, so it is an average of the marginal product of labor and the marginal rate of substitution between consumption and leisure, with a weight $\eta \in (0,1)$ denoting the bargaining power of workers:

$$W_t^* = \eta A_t + (1-\eta)\gamma_n C_t. \tag{10}$$

If wages are flexible—that is, $\rho = 0$—a technology shock raises the wage, consumption, and output in proportion to the level of technology, whereas employment, unemployment, the job finding rate, the number of recruiters, and the recruiter efficiency remain constant. This reflects the offsetting effects of the income and substitution effects of a technology shock on labor supply, as discussed by Blanchard and Galí (2010) and Shimer (2010) in models with a constant labor force. Thus, the same property extends to the model with endogenous labor force participation.[14] Consequently, wage rigidity will play a key role for the propagation of technology shocks in the model.

Labor market clearing requires equality of the household's and firm's accumulation constraints, so

$$f_t U_t = q_t V_t = M_t. \tag{11}$$

The unemployment rate is defined as $u_t = U_t/LF_t$, where $LF_t = N_t + U_t$ is the labor force participation rate. Goods market clearing implies

$$Y_t = C_t. \tag{12}$$

Competitive equilibrium consists of equations (1) $-$ (12). We solve the model by first writing the equilibrium conditions in terms of detrended output, $y_t = Y_t/g^t$, the detrended wage, $w_t = W_t/g^t$, and the detrended target wage, $w_t^* = W_t^*/g^t$, and then deriving a log-linear approximation of the equilibrium conditions for the detrended variables around the balanced-growth path.

4 Quantitative Results

We calibrate the model and evaluate its empirical performance by the dynamic responses to a technology shock and by the results of simulation conditional on technology shocks and discount factor shocks. The successful model reproduces two facts. First, labor force

[14] An increase in consumption following a technology shock raises the cost of job search, as shown by the left hand side of Equation (3); this is the negative income effect. However, the increase in consumption also raises the benefit of job search as shown by the right hand side, which reflects the positive substitution effect. With the household's preferences and the absence of capital in the model, the two effects exactly offset each other.

participation is mildly procyclical, as established by the business cycle literature. Second, technology shocks produce a countercyclical response of labor force participation, as documented in Section 2.

4.1 Calibration

The model is calibrated to monthly frequency, and the calibration is summarized in Table 2. The parameter values in the top panel of the table are taken from Shimer (2013). The value for the subjective discount factor, β, translates to 4.7 percent annually, and the growth rate of technology, g, amounts to 2.2 percent per year. The value for s is the average exit probability from employment to unemployment. The value for q is based on evidence that a recruiter can attract about 25 workers per quarter, or 8.33 per month. The labor force along the balanced-growth path is set at 0.6. Although the labor force participation rate in the U.S. appears to exhibit trend movements, the value of LF does not affect the model's business cycle predictions. The efficiency level of the matching function, μ, is chosen to target a long-run unemployment rate of $u = 0.05$. Then, on the balanced-growth path the job finding rate equals $f = 0.646$, employment equals $N = 0.57$, the number of recruiters equals $V = 0.0023$, and the detrended wage rate is $w = 0.9954$.

Table 2: Calibration of parameters in the monthly model.

β	Subjective discount factor	0.996
g	Long-run growth rate of technology	1.0018
s	Separation rate	0.034
q	Long-run recruiter efficiency	8.33
LF	Long-run labor force	0.6
μ	Efficiency of the matching function	2.3197
ξ	Unemployment elasticity of matching function	0.5
η	Bargaining power	0.5
ρ	Degree of wage rigidity	1
ρ_d	Persistence of discount factor shock	$0.9^{1/3}$
ρ_a	Persistence of technology shock	$0.95^{1/3}$
σ_d	Standard deviation of discount factor shock	0.03
σ_a	Standard deviation of technology shock	0.00032

Wage rigidity is important for the dynamics of labor force participation in the model. As mentioned before, the case of flexible wages ($\rho = 0$) is unable to account for the dynamic responses of employment, unemployment, and labor force participation to a technology shock. Thus, we focus on the case of wage rigidity ($\rho = 1$). A key distinction between these cases is in their implications for the disutility parameters γ_n and γ_u, as demonstrated by Shimer (2013). With flexible wages set by Nash bargaining, the value of γ_n can be determined by the wage equation on the balanced-growth path, and the value of γ_u can in turn be determined by the condition for labor force participation on the balanced-growth path. Under our calibration, the disutility of job search is an order of magnitude smaller than the disutility of work (specifically, $\gamma_n = 1.746$ and $\gamma_u = 0.137$). If $\rho = 1$, however, the wage equation (10) is absent from the model, leaving the two parameters undetermined. We set the ratio $r = \gamma_u/\gamma_n$ so as to produce a countercyclical response of labor force participation to a technology shock that matches the conditional volatility of labor force participation to that observed in the VAR (0.148). This yields a value $r = 0.577$, so job search is only about half as unpleasant as employment. As Shimer (2013) points out, a relatively high disutility of job search is consistent with survey evidence that unemployed workers spend only a small fraction of their time searching for jobs.[15] The levels of γ_n and γ_u are then determined by the balanced-growth condition for labor force participation: $\gamma_n = 1.696$ and $\gamma_u = 0.977$.

The bottom panel of Table 2 presents the calibration of the shock processes. The value of ρ_d is close to and between the values estimated by Smets and Wouters (2003), Galí and Rabanal (2004), and Ireland (2004), and the value of ρ_a is standard in the real business cycle literature. For the standard deviations, the value of σ_d is between the values estimated

[15] Krueger and Mueller (2010) examine the American Time Use Survey and report that unemployed workers spend only about 32 minutes per day on job search. Based on a slightly longer sample period, Campolmi and Gnocchi (2016) report a number of 23 minutes per day.

by Galí and Rabanal (2004) and Ireland (2004).[16] The value of σ_a is chosen to match the standard deviation of output conditional on a technology shock in the model with that in the VAR (0.007).

4.2 Impulse responses analysis

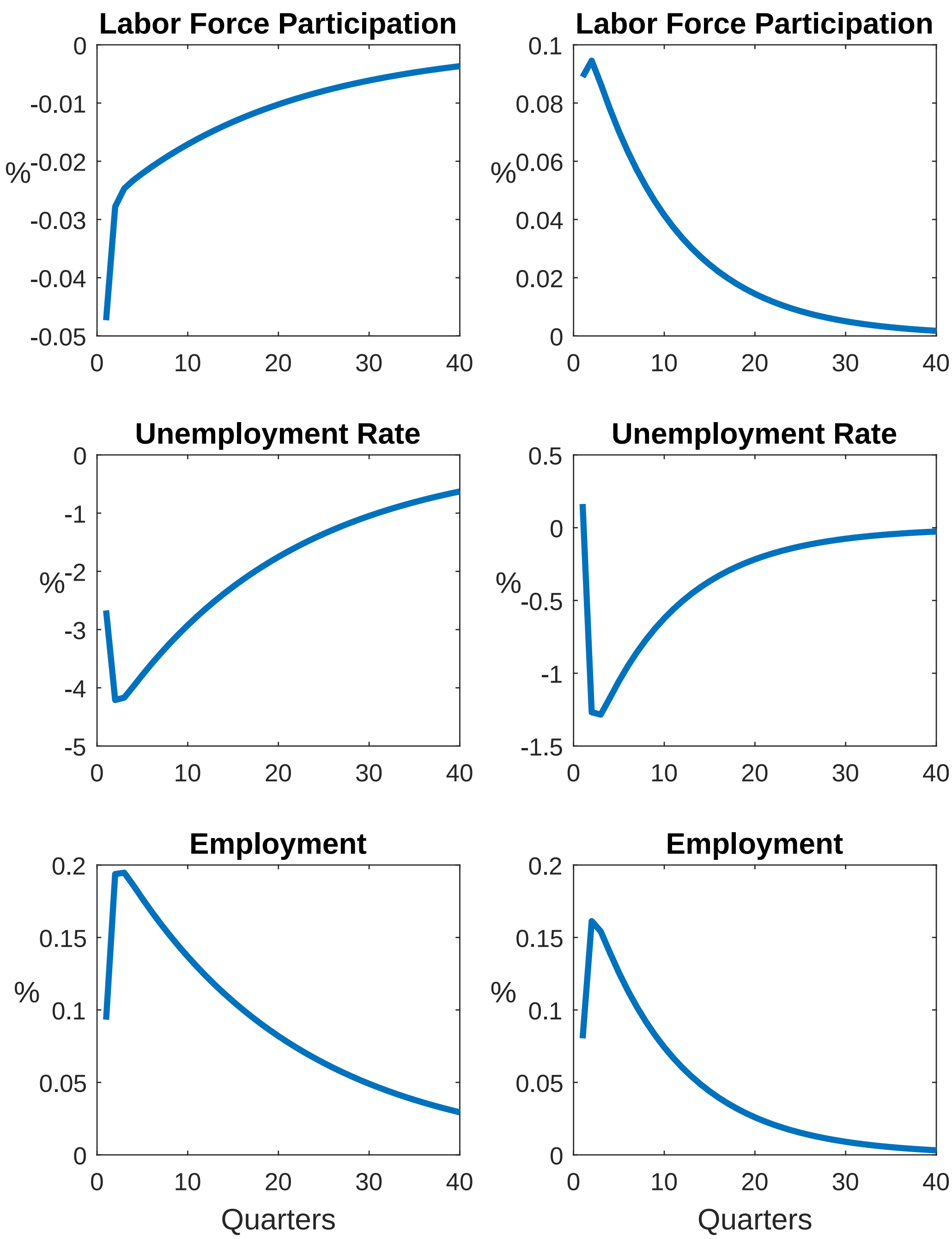
The left column of Figure 3 shows dynamic responses of labor force participation, the unemployment rate, and employment to a one-standard-deviation (positive) technology shock generated by the calibrated model. Monthly responses of the model variables have been aggregated to quarterly frequency. Consistent with the VAR evidence in Figure 2, labor force participation declines modestly, the unemployment rate declines sharply, and employment rises. All else equal, a smaller value of r than the calibrated one would generate a more negative response of labor force participation, whereas the response would become less negative and eventually even positive for higher values of r. Thus, Figure 3 demonstrates that the search model under a reasonable calibration is able to reproduce the empirical responses of labor force participation, the unemployment rate, and employment to a technology shock.

Given the impulse responses to a technology shock, whether the search model can also replicate the unconditional volatilities and correlations of the labor market variables will depend on their responses to a discount factor shock. The right column of Figure 3 shows that an expansionary one-standard-deviation discount factor shock increases labor force participation along with employment, whereas the unemployment rate declines. Thus, the discount factor shock induces procyclical behavior of labor force participation. Moreover, the response of labor force participation to the discount factor shock is larger than the response to the technology shock in absolute value. The relatively strong response of labor force participation

[16] Of these empirical studies, Galí and Rabanal (2004) and Ireland (2004) estimate a consumption preference shock. Smets and Wouters (2003) estimate a discount factor shock, but their estimate of the shock's standard deviation is not comparable to our calibrated value due to a normalization of the shock in their estimation procedure.

Figure 3: Model impulse responses.

Technology shock — Discount factor shock



Notes: The left column shows the impulse responses to a technology shock obtained with the calibrated search model. The right column shows the impulse responses to a discount factor shock.

to discount factor shocks indicates that the procyclical response of labor force participation to such shocks can dominate the countercyclical response to technology shocks.[17]

To see why the response of labor force participation to a technology shock or discount factor shock depends on the ratio of disutilities, r, we simplify the labor force participation condition (3) by dividing both sides by C_t:

$$\frac{\gamma_u}{f_t} = \beta E_t \frac{e^d_{t+1}}{e^d_t} \left[\frac{W_{t+1}}{C_{t+1}} - \gamma_n + (1-s)\frac{\gamma_u}{f_{t+1}} \right].$$

This equilibrium condition requires the expected cost of job search expressed in terms of utility to equal its expected benefit. For the sake of intuition we consider the household's labor force participation decision when γ_u is small or large, where those magnitudes should be interpreted as relative to the size of γ_n.

Consider first the effects of a positive technology shock. The ensuing increase in hiring raises the job finding rate f_t, thus lowering the expected cost of job search. For small (large) values of γ_u, the rise in the job finding rate will induce a small (large) decline in the expected cost of job search, since $D(\gamma_u/f_t) = -\gamma_u/f_t^2$. Assuming wages are rigid, the persistent shock also lowers the expected benefit of job search by reducing the future marginal utility of consumption, $1/C_{t+1}$, and raising the future job finding rate, f_{t+1}. The effect of the job finding rate on the foregone future search cost—the second component of the expected benefit of job search—also depends on the value of γ_u. However, because the expected benefit consists of two components, it is less sensitive to the value of γ_u than the expected cost. Therefore, if the value of γ_u is small, the shock tends to induce a small decline in the expected cost of job search relative to the decline in the expected benefit. Then, as the expected cost exceeds the expected benefit the household reduces the number of job searchers, which boosts the job finding rate until the expected cost equals the expected benefit. Labor force participation declines. Conversely, if γ_u is large, the expected cost of

[17]Consistent with the predictions of our calibrated model, the calibrated DSGE model of Campolmi and Gnocchi (2016) produces a modest decline in labor force participation following a positive technology shock, and a larger increase in participation following an expansionary preference shock.

job search tends to fall by more than the expected benefit after the shock, so the household increases the number of job searchers, which dampens the job finding rate, until the expected cost and benefit are equal. This increases labor force participation.[18]

The intuition for the effect of a discount factor shock on labor force participation is similar to that for a technology shock, except that the discount factor shock has a direct impact on the present value of the expected benefit of job search. Indeed, an expansionary discount factor shock increases the ratio e_{t+1}^d/e_t^d, thus boosting the present value of the expected benefit. As a result, a given value of γ_u induces a larger (that is, more positive or less negative) response of labor force participation to a discount factor shock than to a technology shock.

4.3 Simulation results

To verify to what extent the search model can reproduce the conditional and unconditional moments of the U.S. labor market data we turn to model simulations. Table 3 reports volatilities and correlations of the labor market variables that are comparable to the empirical moments shown in Table 1.

Turning first to the comparison of the conditional moments, line 3 presents the standard deviations of labor force participation, the unemployment rate, and employment relative

[18] Regarding the role of wage rigidity, if $\rho \in (0,1)$ the equation for the target wage and the condition for labor force participation determine $r = 0.078$ (=0.137/1.746). With such a low value for r, the discussion indicates that if ρ is close to one, a positive technology shock will induce a labor force response that is too small. As ρ gets smaller, the increasing responsiveness of the wage to shocks dulls the firm's incentive to recruit. Moreover, for positive but small enough values of ρ, the responsiveness of the wage to shocks leads the discouragement effect to dominate the added worker effect on the household's job search decision. As a result, the unemployment rate can become procyclical as higher wages prompt the household to shift many members to job search. The anomaly of procyclical unemployment reflects an earlier finding by Tripier (2003) that endogenizing labor force participation in a search model with Nash bargaining renders the unemployment rate either procyclical or acyclical.

to that of output, and line 4 presents the correlations with output. The relative standard deviation of labor force participation matches its empirical counterpart as this statistic was the calibration target for the ratio of disutilities, r. The model predicts larger volatility of the unemployment rate and employment conditional on technology shocks than is evident from the VAR. Thus, the volatility of labor force participation is considerably smaller than that of employment, consistent with the VAR evidence. As for the correlations, the model generates strongly countercyclical labor force participation, a strongly countercyclical unemployment rate, and strongly procyclical employment. While the correlation of employment is larger than its counterpart from the VAR, the correlations of labor force participation and unemployment are close to the VAR-based ones. Note that, although the calibration of r ensured a decline (rise) in labor force participation following a positive (negative) technology shock, the strongly negative correlation that is close to its empirical counterpart is a result delivered by the calibrated model.

Table 3: Business cycle statistics of the model.

	Variable X	LF	UR	E
1.	Std(X)/Std(Y)	0.365	17.515	0.975
2.	Corr(X,Y)	0.285	-0.941	0.999
3.	Std(X)/Std(Y)	0.148	20.445	0.946
4.	Corr(X,Y)	-0.856	-0.997	1.000

Notes: Lines 1 and 2 report business cycle statistics generated by simulating the calibrated model with technology shocks and discount factor shocks. Lines 3 and 4 report statistics of data generated by simulating the calibrated model conditional on technology shocks only. The simulations comprise 5,000 histories of 798 months each. Each monthly series is aggregated to quarterly frequency and detrended with the HP filter ($\lambda = 10^5$). Y, LF, UR, and E denote output, labor force participation, the unemployment rate, and employment, respectively.

Lines 1 and 2 of Table 3 present the unconditional volatilities and correlations predicted by the model. While the relative standard deviations are all higher than their empirical counterparts in Table 1, the model generates a fairly small standard deviation of labor force participation. Consistent with the evidence, the volatility of labor force participation is less than half that of employment. Furthermore, the model successfully replicates the mildly procyclical labor force participation rate along with a strongly countercyclical unemployment rate and strongly procyclical employment.

The results also highlight that the two shocks have differing effects on the unemployment rate. While the conditional and unconditional volatilities of employment in the model are similar, the conditional volatility of the unemployment rate is larger than the unconditional one. This reflects that employment gains driven by technology shocks are accompanied by relatively large declines in unemployment, as labor force participation falls. In contrast, employment gains driven by discount factor shocks are accompanied by relatively small declines in unemployment aided by increased labor force participation. Thus, the countercyclical response of labor force participation to a technology shock leads the unemployment rate to overstate the downturn or upturn in employment, whereas the procyclical response of labor force participation to a discount factor shock leads the unemployment rate to understate the movements in employment.

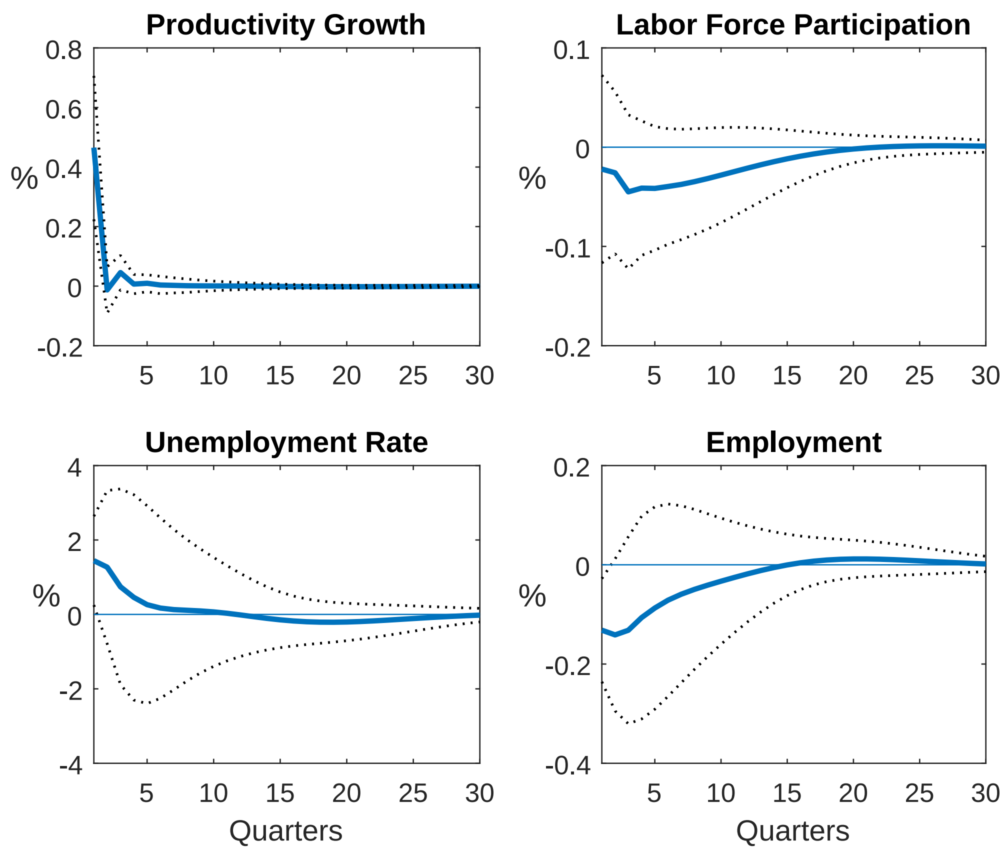
In sum, while the calibrated model overpredicts the volatilities of labor market variables relative to output, it successfully generates a smaller volatility of labor force participation than of employment. The model also successfully generates the countercyclical response of labor force participation to technology shocks along with its overall mild procyclical behavior.

5 Long-run identifying restrictions

The evidence in Section 2 is based on short-run identifying restrictions for the technology shock. An alternative identification method for the structural technology shock imposes long-run restrictions.[19] Blanchard and Quah (1989), who pioneered this method, found that unemployment rises after a positive permanent shock to output. Using the same identification

[19] Christiano, Eichenbaum, and Vigfusson (2007) provide an econometric argument in favor of short-run restrictions. They assess structural VARs and find that they perform well when identification is based on short-run restrictions, but that sampling uncertainty associated with estimated impulse responses is substantially larger based on long-run restrictions.

Figure 4: Empirical impulse responses to a technology shock: long-run identifying restrictions.



Notes: The solid lines are impulse responses obtained by estimating a structural VAR during the period 1952:Q1–2018:Q2 on the logarithm of the first difference of labor productivity and the logarithms of the unemployment rate, the labor force participation rate, and the employment-population ratio. The lag length of the VAR is two quarters as determined by the Schwarz criterion. Labor productivity is measured as real GDP divided by civilian employment. The technology shock is identified using the method of Blanchard and Quah (1989). The dashed lines are ± 2-standard-deviations confidence intervals obtained from $1,000$ bootstrap replications of the VAR.

scheme, Galí (1999) showed that hours worked decline after a positive technology shock. Though the finding of a contractionary effect of technology shocks proved controversial, Fernald (2007) showed that it is a robust finding once the low-frequency movements are removed from productivity growth prior to estimation of the VAR.[20]

To check the robustness of our empirical finding for labor force participation, we estimate a VAR on the first difference of productivity and the levels of labor force participation, the unemployment rate, and employment. As before, variables are detrended using the low-frequency HP filter. The logarithm of productivity is differenced before the trend is removed from the differenced series, in line with Fernald's (2007) recommendation of removing the low-frequency movements from productivity growth. The structural technology shock is recovered via the identifying assumption that no other shocks affect productivity in the long run.

A technology shock that permanently raises productivity produces a rise in the unemployment rate and a decline in employment in the short run, as shown in Figure 4. This is consistent with the findings of Galí (1999), Fernald (2007), and others. Labor force participation declines in the short run, in line with its response in the main empirical result displayed in Figure 2. Thus, our new empirical finding is robust to whether technology shocks are identified with short-run or long-run restrictions. In the case of long-run restrictions, participation declines as the effect of the decline in employment outweighs the effect of the rise in the unemployment rate. In both cases, however, the results indicate that in the short run, the added worker effect of a technology shock on labor force participation outweighs the discouragement effect.

Our search model with labor force participation appears at odds with the positive effect of technology shocks on unemployment obtained with long-run restrictions. The evidence obtained with the long-run restrictions may call for an extension of the model that incorpo-

[20]Basu, Fernald, and Kimball (2006) construct an alternative measure of technology change and confirm the contractionary effect of technology improvements.

rates nominal price rigidities, as Galí (1999) points out. Such an extended model would allow only a minor role for technology shocks, because it would have to reconcile (i) the procyclical response of unemployment to a technology shock with the countercyclicality of unemployment, and (ii) the countercyclical response of labor force participation to a technology shock with the procyclicality of labor force participation.

6 Conclusion

This paper has presented new evidence based on VAR analysis that labor force participation declines in the short run following a positive technology shock. The highly countercyclical response of labor force participation to a technology shock contrasts with the well documented mild procyclical behavior of labor force participation in the business cycle. The paper also showed that a search model of the labor market that incorporates a participation choice can interpret the evidence. A positive technology shock temporarily reduces labor force participation under a reasonable calibration, whereas discount factor shocks induce a procyclical response of labor force participation. As a result, the model can generate both the countercyclical response to technology shocks and the procyclical behavior. The evidence that labor force participation declines after the technology shock is obtained regardless of whether the shock is identified with short-run or long-run identifying restrictions.

Our results indicate nontechnology shocks play an important role in explaining labor market fluctuations. The vast labor market search literature based on the ideas of Diamond (1982) and Mortensen and Pissarides (1994) focuses primarily on technology shocks as the sole driving force of labor market fluctuations. The technology-driven view reflects the real business cycle model that dominated business cycle research at the time the search model was developed, but the business cycle literature has since moved on to consider a variety of other shocks. Our paper indicates that considering other shocks for explaining labor market fluctuations is a promising avenue for future research based on search models.

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