Lending Relationships and Labor Market Dynamics *

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Abstract

Motivated by a negative link between credit spreads and labor force participation (LFP) and a positive link between these spreads and unemployment over the business cycle, we study the role of LFP as an amplification mechanism of financial shocks in a labor search model with endogenous LFP, lending relationships, and credit-market disruptions. Amid aggregate productivity and financial shocks that replicate the empirical volatility of LFP and credit spreads, the model produces highly volatile unemployment and vacancies, countercyclical credit spreads and unemployment, and procyclical LFP. When we quantitatively match the cyclical behavior of credit spreads, the interaction between endogenous LFP and financial shocks gives rise to much sharper vacancy fluctuations and plays a key role in generating quantitatively factual cyclical labor market dynamics.

JEL Classification: E24, E32, E44.

Keywords Unemployment, endogenous labor force participation, financial shocks, deep habits in credit markets, lending relationships.

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1 Introduction

Financial shocks play an important role in shaping U.S. aggregate fluctuations (Jermann and Quadrini, 2012). Several recent studies have documented a strong link between financial conditions, aggregate economic activity, and labor markets (Amiti and Weinstein, 2011; Boeri et al., 2013; Greenstone et al., 2014; Haltenhoff et al., 2014; Duygan-Bump et al., 2015; and Cingano et al., 2016; Epstein, Finkelstein Shapiro, and González Gómez, 2017; Eckstein et al., 2019). The majority of existing studies on cyclical financial conditions and labor markets center on labor-demand factors, with labor force participation (LFP)—a labor-supply factor—receiving little attention as a potential amplification mechanism amid credit-market disruptions. This immediately raises two questions. First, what are the effects of financial *shocks*, if any, on LFP? Second, how do cyclical movements in LFP affected by financial disturbances contribute to cyclical labor market dynamics?

In this paper, we document that over the business cycle, credit spreads are strongly and positively correlated with unemployment *and* negatively correlated with LFP and job vacancies. These facts are complemented by VAR-based evidence showing that an increase in credit spreads generates a non-trivial increase in unemployment and a decrease in vacancies and LFP. Motivated by these facts, we build a labor search framework with endogenous LFP, long-lasting credit relationships rooted in deep habits, and financial shocks to assess the role of LFP as an amplification mechanism of financial shocks in the labor market. Conditional on matching the empirical volatility of LFP and credit spreads, the model generates highly volatile unemployment and job vacancies that are quantitatively consistent with the data. Moreover, this occurs in a context with strongly countercyclical credit spreads and unemployment, and factual macroeconomic dynamics. Comparing our framework to a more standard environment that abstracts from endogenous LFP shows that the interaction between endogenous movements in LFP and credit relationships represents a powerful amplification mechanism of financial shocks that results in considerably higher labor market volatility, *even as both frameworks capture exactly the same volatility and countercyclicality of credit spreads in the data*. Our findings highlight the role of endogenous LFP—a labor-supply (as opposed to labor-demand) factor–for better understanding the cyclical behavior of labor markets in a context where financial shocks shape business cycle fluctuations.

In our framework, households make LFP decisions and firms post vacancies to hire workers and develop long-term credit relationships with lenders—reflected in deep habits—to finance their working capital expenditures. By introducing a tradeoff between lenders' present and future profits, deep habits and long-lasting credit relationships generate endogenously countercyclical credit spreads, act as a channel through which financial shocks affect labor market and aggregate dynamics, and amplify the economy's labor market response to shocks. To better understand how LFP amplifies financial shocks and leads to greater unemployment and vacancy volatility, consider an adverse financial shock. This shock generates an increase in credit spreads, which raises firms' working-capital costs and leads to an *initial* reduction in job vacancies. All else equal, the fall in vacancies puts downward pressure on wages, which reduces household members' benefit of labor market participation and induces a reduction in participation. Importantly, the fall in participation translates into a reduction in the pool of potential workers that firms face. A smaller labor force reduces the perceived extent to which firms can find workers and fill vacancies, which increases their expected costs of vacancy posting by more relative to an environment with constant LFP. This last fact ultimately leads to a considerably deeper contraction in vacancies that, in turn, contributes to a much sharper expansion in unemployment. These model dynamics are consistent with VAR-based evidence. While the model mechanism just described is also operational amid aggregate productivity shocks, the inclusion of financial shocks is central to quantitatively generating the high volatility of credit spreads in the data. In turn, this factual credit-market volatility is behind the quantitative success of our framework.

Our work is closest to recent business cycle studies on the interaction between financial and labor market frictions. Chugh (2013) and Petrosky-Nadeau (2014) show that countercyclical credit spreads increase the volatility of unemployment and vacancies amid TFP shocks compared to standard search models. Monacelli, Quadrini, and Trigari (2012) highlight the role of financial frictions in affecting wage-setting and unemployment. Garín (2015) shows that an RBC search model with collateral constraints and financial shocks can capture almost 50 percent of the empirical volatility of unemployment.[1] Epstein, Finkelstein Shapiro,

[1]Papers on the limited volatility of unemployment in standard search models *in a context that abstracts*

and González Gómez (2017) show that the interaction between on-the-job search and financial frictions *and* shocks amid empirically-consistent TFP and financial disturbances can quantitatively reproduce the cyclical dynamics of U.S. labor market and aggregate variables. Our work also emphasizes the importance of countercyclical spreads and financial shocks for U.S. labor market dynamics but, unlike existing studies, goes a step further by: (1) stressing the relevance of countercyclical spreads *alongside* financial shocks that replicate the volatility of spreads in the data; and (2) pointing to the role of LFP as a strong amplification channel of financial shocks.

Using a model based on Bernanke, Gertler, and Gilchrist (1999) (henceforth BGG), Mumtaz and Zanetti (2016) stress the role of labor market frictions in amplifying or limiting the impact of financial frictions depending on the type of shock, but abstract from assessing the role of financial frictions in the cyclical behavior of unemployment. Zanetti (2019) incorporates job-destruction shocks and frictions in firms' ability to raise funds into a standard search model, showing that these shocks are important for rationalizing the cyclical dynamics of unemployment in the data. Eckstein et al. (2019) introduce default, interest rate shocks, and vacancy costs subject to working capital constraints into a standard search model. In the presence of factually-volatile corporate interest rates, their framework can capture roughly 80 percent of the empirical volatility of unemployment and market tightness. Critically, these studies abstract from LFP, where this component is a central feature of our analysis. Our work therefore complements Zanetti (2019) and Eckstein et al. (2019) by highlighting a complementary channel rooted in endogenous LFP through which financial shocks are amplified and contribute to greater unemployment and job-vacancy volatility. Finally, our interest in LFP is related to recent theoretical studies that incorporate this margin into search frameworks with frictionless credit markets (Erceg and Levin, 2014, Krusell et al., 2017, and Ferraro and Fiori, 2019, among others).[2]

The fundamental distinctions between these studies and our work are twofold. First, we focus on participation as an amplification channel of financial shocks that complements

from financial frictions include, among others, Mortensen and Nagypal (2007) and Ljungqvist and Sargent (2017), who stress the role of surplus-sharing, Zanetti (2007), who highlights the role of labor market institutions, and more prominently Hagedorn and Manovskii (2008), among others.

[2]Both Krusell et al. (2017) and Ferraro and Fiori (2019) generate procyclical participation, as in the data.

other mechanisms in the literature. Second, we combine endogenous LFP and deep habits in lending in an environment with financial shocks. Our choice of modeling credit frictions via lending relationships amid labor market frictions is related to Wasmer and Weil (2004), whose work explores the link between search-based credit relationships and labor market frictions. The main rationale for introducing credit frictions via habit formation, which stands in contrast to Wasmer and Weil (2004), is simple: these frictions are able to accommodate highly volatile credit spreads, which are not only a feature of the data but also critical for assessing the impact of the cyclical behavior of credit spreads on labor market dynamics and the amplification mechanism of LFP *quantitatively.* While alternative financial frictions rooted in asymmetric information also generate countercyclical spreads (for example, BGG), the implied volatility of spreads under plausible calibrations of these models is at least an order of magnitude lower than in the data. In contrast, habit formation in credit markets (which ultimately also embodies a notion of asymmetric information), allows us to *quantitatively* capture both the cyclicality *and* volatility of spreads in the data.[3] All told, given our interest in the quantitative relevance of the volatility of credit markets for labor market dynamics, these features provide a strong rationale for using financial frictions rooted in deep habits.

The rest of the paper is structured as follows. Section 2 presents empirical and VAR-based evidence on the relationship between credit spreads, unemployment, and LFP over the business cycle. Section 3 describes the model. Section 4 presents our quantitative results. Section 5 concludes.

[3]Several well-known studies in banking provide empirical support for the mechanisms rooted in deep habits, whereby the presence of an information monopoly lets lenders charge higher interest rates to their "locked-in" borrowers during recessions (Diamond, 1984; Sharpe, 1990; Rajan, 1992; von Thadden, 1995; Dell'Ariccia, 2001; and Santos and Winton, 2008).

2 Empirical Motivation

2.1 Unconditional Cyclical Correlations: Credit Spreads and Labor Markets

Using U.S. data that spans the period 1987Q1-2017Q4, Table 1 shows unconditional cyclical correlations of the unemployment rate, job vacancies, and the labor force participation (LFP) rate with the credit spread, where the latter is defined as the difference between BAA bond yields and the U.S. federal funds rate (see Appendix A for more details on sources).[4] Our focus on post-1985 data is in line with related studies, which abstract from the structural changes in business-cycle and financial-market volatility that took place after the wave of regulatory changes in the mid-1980s (McConnell and Perez-Quiros, 2000; Jermann and Quadrini, 2012; Liu, Theodoris, Mumtaz, and Zanetti, 2018). We present these facts using Hodrick-Prescott (HP)-filtered data (with smoothing parameter 1600) and also show results using the Baxter-King (BK) band-pass filter with quarterly data for completeness.[5].

Consistent with existing business-cycle work, an increase in credit spreads, which reflects a deterioration in credit conditions, is associated with higher unemployment and a reduction in vacancies. We complement these facts by showing that an increase in credit spreads is associated with lower LFP. Table B in Appendix B shows the cyclical correlations between contemporaneous and lagged values of credit spreads and unemployment, vacancies, and LFP, and confirms that changes in credit spreads lead changes in the labor market.

[4]In the remaining of the paper, LFP refers to the labor force participation *rate* unless otherwise noted.

[5]Table A1 in Appendix B confirms the same stylized facts using the Butterworth and Christiano-Fitzgerald filters.

	Unempl. Rate	**Part. Rate**	**Vacancies**
HP-Filtered Data			
Credit Spread	0.5823*	-0.3092*	-0.5987*
	(0.0000)	(0.0000)	(0.0000)
BK-Filtered Data			
Credit Spread	0.5971*	-0.3179*	-0.7181*
	(0.0000)	(0.0000)	(0.0000)

Sources: Saint Louis FRED Database and Barnichon (2010). Notes: Unempl. Rate is the civilian unemployment rate and Part. Rate is the LFP rate. Vacancies are measured by job openings as in Barnichon (2010). The cyclical component of each series is obtained using a Hodrick-Prescott (HP) filter with smoothing parameter 1600 or a Baxter-King (BK) band-pass filter at a quarterly frequency. See Appendix A for additional details on the variables and sources. P-values in parentheses. A * denotes significance at the 5 percent level.

Table 1: Cyclical Correlations between Labor-Market Measures and Credit Spreads (1987Q1-2017Q4)

2.2 Structural VAR-Based Evidence

Empirical Model Specification To provide supporting evidence on the link between credit spreads, unemployment, vacancies, and LFP beyond simple unconditional cyclical correlations, we estimate the following structural vector autoregression (SVAR):

$$X_t = \alpha + \sum_{l=1}^{4} \Gamma(l) X_{t-l} + \mu_t, \tag{1}$$

where $X_t \equiv [s_t, ur_t, p_t, v_t, y_t]'$ is the vector of endogenous variables, s is the credit spread, ur is the unemployment rate, p is the LFP rate, v are vacancies, and y is real GDP (in logs). We adopt four lags in the polynomial $\Gamma(l)$ (this is consistent with the use of quarterly data and broadly in line with related studies, such as Fujita and Ramey, 2007; alternative lags do not change our findings). In equation (1), $\mu_t \equiv [\mu_t^s\, \mu_t^{ur}\, \mu_t^p, \mu_t^v, \mu_t^y]'$ is the vector of reduced-form residuals, which are allowed to be contemporaneously correlated with each other.

The elements in μ_t are expressed as a linear combination of the structural shocks and the remaining reduced-form residuals as follows:

$$\mu_t^s = \alpha_{sur}\mu_t^{ur} + \alpha_{sp}\mu_t^p + \alpha_{sv}\mu_t^v + \alpha_{sy}\mu_t^y + e_t^s, \tag{2}$$

$$\mu_t^{ur} = \alpha_{urs}\mu_t^s + \alpha_{urp}\mu_t^p + \alpha_{urv}\mu_t^v + \alpha_{ury}\mu_t^y + e_t^{ur}, \tag{3}$$

$$\mu_t^p = \alpha_{ps}\mu_t^s + \alpha_{pur}\mu_t^{ur} + \alpha_{pv}\mu_t^v + \alpha_{py}\mu_t^y + e_t^p, \tag{4}$$

$$\mu_t^v = \alpha_{vs}\mu_t^s + \alpha_{vur}\mu_t^{ur} + \alpha_{vp}\mu_t^p + \alpha_{vy}\mu_t^y + e_t^v, \tag{5}$$

$$\mu_t^y = \alpha_{ys}\mu_t^s + \alpha_{yur}\mu_t^{ur} + \alpha_{yp}\mu_t^p + \alpha_{yv}\mu_t^v + e_t^y, \tag{6}$$

where $e_t \equiv [e_t^s\, e_t^{ur}\, e_t^p\, e_t^v, e_t^y]'$ are the structural shocks with mean zero and $E_{e_t,e_k'} = \Sigma_e,\ t = k$.

Baseline Identification Assumptions This VAR has 25 coefficients to estimate: the 20 coefficients in the system (2)-(6) and the 5 variances of the structural shocks in e_t. With the variance-covariance matrix providing 15 moments that can be used to estimate this set of coefficients, 10 restrictions are needed to identify the structural shocks.

First, we assume that no endogenous variable in the system affects LFP contemporaneously. This assumption is intuitive given that labor markets often respond with a lag to changes in economic (including credit) conditions, and yields 4 identification restrictions: $\alpha_{ps} = \alpha_{pur} = \alpha_{pv} = \alpha_{py} = 0$. Second, credit spreads can affect vacancies within one period, which is consistent with search models, but spreads do not affect unemployment (an equilibrium labor market outcome) or output contemporaneously within one quarter. This assumption gives us two more identification restrictions: $\alpha_{urs} = \alpha_{ys} = 0$. Third, we assume that while changes in LFP can affect potential GDP, they do not affect output contemporaneously, so that $\alpha_{yp} = 0$ (this assumption is consistent with recent empirical literature on workers' transitions from non-participation directly into employment; see Beffy et al., 2014, and Hall and Kudlyak, 2019, among others). Fourth, since vacancies are a firm's choice and LFP is a household's choice and two different actors are making these choices at any given point in time, they do not affect each other contemporaneously within a quarter, so that $\alpha_{vp} = 0$. Fifth, output is an endogenous equilibrium outcome that does not affect a firm's choice of vacancies within a given quarter, so that $\alpha_{yv} = 0$. Finally, vacancies determine contemporaneously the number of job openings but not the number of hires and separations, all of which are factors that influence productivity and output, so that $\alpha_{yv} = 0$. These restrictions, which we adopt as a baseline, are intuitively plausible or guided by theory. For robustness, Appendix C presents results based on an alternative and similarly plausible set of restrictions.[6]

Granger Causality Tests Before presenting our main results, we conduct Granger causality tests based on our baseline VAR. Per Table A3 in Appendix C, we reject the hypothesis that, conditional on lagged values of the dependent variables, the four lags of the credit spread do not Granger-cause unemployment, vacancies, or LFP.

Note: 90-percent confidence bands are computed using standard bootstrap methods.

Figure 1: Response of Unemployment Rate, Labor Force Participation Rate, and Vacancies to an Initial Structural Shock to Credit Spreads

Credit-Spread Shock Figure 1 shows the response of the unemployment rate, vacancies, and LFP to an initial 1-percentage-point structural positive shock to credit spreads. Of

[6]Importantly, given our interest in the impact of *an increase in credit spreads* on labor market variables, we focus solely on identification restrictions that deliver an increase in credit spreads *after having taken into account the feedback effect between the labor market and spreads.*

note, even though we consider a one-percentage-point credit-spread shock, the spread does not increase by one percentage point on impact because, given our identification assumptions, the spread depends endogenously on the response of the other variables in the VAR system, so that its impact response is, in fact, smaller than 1 percentage point.

An increase in credit spreads leads to a persistent increase in the unemployment rate, to a sharp reduction in vacancies, and to a persistent fall in LFP. Figure A1 in Appendix C shows that the broad patterns in Figure 1 remain unchanged under an alternative and similarly plausible set of identification restrictions.[7]

VAR Forecast Errors To provide complementary evidence on the link between credit market conditions and labor markets, we follow den Haan (2000) and characterize the co-movement between the unemployment rate, LFP, and spreads at business cycle frequencies by looking at the correlation of VAR forecast errors at various time horizons.[8]

Formally, we estimate the following VAR:

$$X_t = \alpha + \mu t + \sum_{l=1}^{4} \beta_l X_{t-l} + \sum_{i=1}^{3} \theta_i Q_{i,t} + \epsilon_t, \tag{7}$$

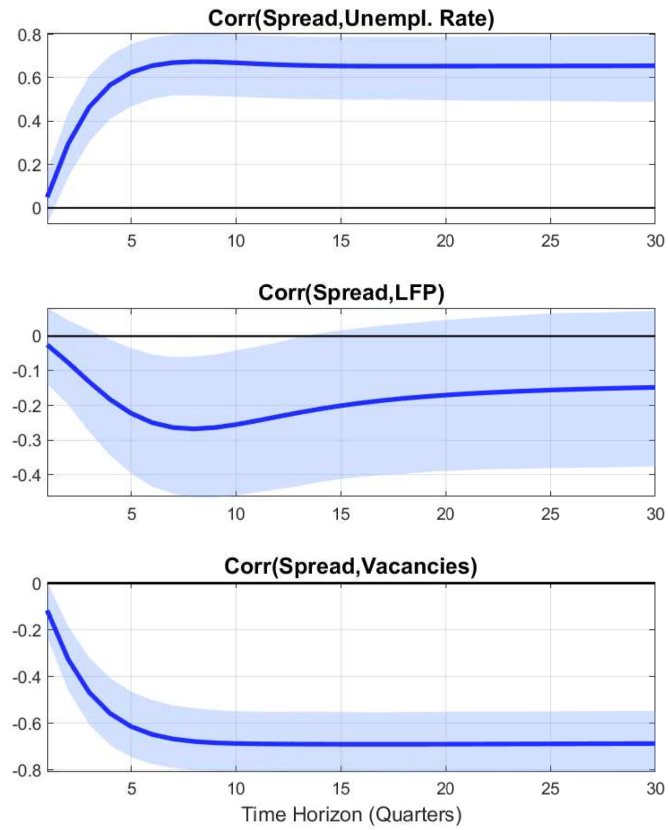
where X_t is a vector of endogenous variables that includes real GDP growth, the credit spread, and the unemployment rate, vacancies or LFP depending on which labor market variable we are considering. t is a linear time trend. The Q matrix includes quarterly dummy variables to control for seasonality and we adopt four lags (our main conclusions do not change with an alternative number of lags).

Figure 2 plots the correlations of the VAR forecast errors between credit spreads and: the unemployment rate, LFP, and vacancies for various forecast horizons (Appendix C provides more details on the computation of these correlations). The figure shows that an increase in lending spreads is unambiguously associated with an increase in unemployment and a

[7]Specifically, we replace the restriction that $\alpha_{yv} = 0$ with $\alpha_{sp} = 0$, so that the spread does not respond to LFP contemporaneously.

[8]This approach provides particular advantages compared to raw correlations for studying business cycle comovement because correlation coefficients are defined only for stationary series and are therefore sensitive to the detrending methodology used. In contrast, the VAR can contain any combination of stationary processes and processes integrated of arbitrary order (Aliaga-Díaz and Olivero, 2010b).

reduction in vacancies and LFP, which is consistent with the raw unconditional cyclical correlations in Table 1.



Notes: LFP denotes the labor force participation rate. 90-percent confidence bands (in light blue) are computed using 2500 replications.

Figure 2: Correlations of VAR Forecast Errors at Various Horizons: Credit Spreads, Unemployment, Labor Force Participation, and Vacancies

All told, the facts and empirical evidence above confirm a strong link between credit spreads (which embody financial conditions), and unemployment, vacancies, and LFP over the business cycle.

3 The Model

We incorporate frictional credit markets via deep habits in lending relationships as in Aliaga-Díaz and Olivero (2010a) into an RBC search and matching model with endogenous labor force participation (LFP) in the spirit of Arseneau and Chugh (2012). The economy has a population of unit mass and is comprised of households that make LFP decisions, financial intermediaries, and firms. Firms finance their costs—comprised of the wage bill, physical capital purchases, and vacancy-posting costs—with external resources by developing endogenously-persistent lending relationships with monopolistically-competitive lenders. Combined with financial shocks, this structure can deliver countercyclical and highly volatile credit spreads that are quantitatively consistent with the data.[9]

3.1 Households

There is a representative household with a measure one of members. The household is the ultimate owner of both firms and financial intermediaries. It supplies deposits to financial intermediaries, rents capital out to firms, and supplies labor to firms in frictional labor markets by making LFP decisions. As such, LFP is endogenous. At any given point in time, household members can be in one of three different states: employed by firms (n), unemployed and actively searching for a job (s), or outside of the labor force. Following the literature, there is perfect risk-pooling between household members within the household (Merz, 1995; Andolfatto, 1996).

Formally, the household chooses consumption c_t, capital accumulation k_{t+1}, bank deposits d_t, desired employment n_t, and the measure of household members who search for employment s_t to maximize $E_0 \sum_{t=0}^{\infty} \beta^t \{u(c_t) - h[(1-f(\theta_t))s_{ht} + n_t]\}$ subject to the budget constraint

$$c_t + d_t + inv_t + T_t = w_t n_t + r_t k_t + \chi(1-f(\theta_t))s_{ht} + R_{d,t-1}d_{t-1} + \Pi_t, \tag{8}$$

[9]Our modeling approach is not meant to assess the response of banks to financial crises or other periods of severe distress in credit markets, which often times are accompanied by large losses among financial intermediaries, heightened default risk (or actual default), and highly nonlinear dynamics. Models that are better suited for the analysis of those particular events, which is not the main objective of our work, include, for example, Gertler and Karadi (2011).

and the laws of motion of capital and employment

$$k_t = (1-\delta)k_{t-1} + inv_t, \tag{9}$$

$$n_t = (1-\rho^n)n_{t-1} + s_{ht}f(\theta_t), \tag{10}$$

where $u'(\cdot) > 0, u''(\cdot) < 0$, $h'(\cdot) > 0, h''(\cdot) > 0$, $lfp_t \equiv [(1-f(\theta_t))s_{ht} + n_t]$ is the level of LFP. Given that the population is normalized to 1, lfp_t is also the LFP *rate*. The household pays lump-sum taxes T_t and receives lump-sum profits from ownership of firms and financial intermediaries $\Pi_t = \int_0^1 \pi_{i,t}di + \int_0^1 \pi_{j,t}dj$, where i and j are used to index firms and intermediaries, respectively. w_t and r_t denote the real wage and capital rental rates, respectively. χ is the flow value of unemployment benefits, $f(\theta_t)$ is the endogenous job-finding probability (a function of market tightness θ_t), and ρ^n is the exogenous job separation probability. R^d is the real gross deposit rate, and $0 < \delta < 1$ is the exogenous capital depreciation rate. Following Arseneau and Chugh (2012), new matches in period t become active in the same period.

The household's first-order conditions yield standard Euler equations for deposits and capital, $u'(c_t) = \beta E_t u'(c_{t+1})R_{d,t}$ and $u'(c_t) = \beta E_t u'(c_{t+1})\left[r_{t+1} + (1-\delta)\right]$, whereby households equate the marginal cost of saving to the expected marginal benefit of holding deposits, and the marginal cost of saving to the expected marginal benefit of an additional unit of capital, respectively. An optimal LFP condition also obtains:

$$\frac{h'(lfp_t)}{u'(c_t)} = f(\theta_t)\left[w_t + (1-\rho^n)E_t\left(\beta\frac{u'(c_{t+1})}{u'(c_t)}\right)\left(\frac{1-f(\theta_{t+1})}{f(\theta_{t+1})}\right)\left(\frac{h'(lfp_{t+1})}{u'(c_{t+1})} - \chi\right)\right] + (1-f(\theta_t))\chi. \tag{11}$$

This condition implies that households equate the marginal cost of participating in the labor market to the expected marginal benefit. The latter is given by the real wage and the future expected value of the employment relationship if a match with a firm occurs with probability $f(\theta_t)$, and the flow contemporaneous value of unemployment benefits χ, which a household member receives with probability $(1-f(\theta_t))$. This last condition is identical to the one in Arseneau and Chugh (2012). For future reference, the household's stochastic discount factor is $\Xi_{t+1|t} \equiv \beta u'(c_{t+1})/u'(c_t)$ and the unemployment *rate* is the ratio of unsuccessful searchers to the labor force, $ur_t = (1 - f(\theta_t))s_{ht}/lfp_t$.

Of note, in Arseneau and Chugh (2012) and incidentally in our model, LFP is $lfp_t \equiv [(1 - f(\theta_t))s_{ht} + n_t]$. As such, the household's choice over s_{ht} should be interpreted as a choice over the measure of household members who search for jobs, and *not* as a choice over search effort (or time spent searching for employment) for a given member. Indeed, in our context, search effort for a member who is unemployed and searching for a job is constant, implying that the measure of unemployed household members who are searching is $(1 - f(\theta_t))s_{ht}$. This subtle distinction between search behavior and search effort in a framework with endogenous LFP is important to point out since it supports our focus on the cyclical behavior of LFP in the data as opposed to individual search effort.

3.2 Firms

There is a continuum of firms indexed by i on the unit interval. Firm i uses capital k_{it} and labor n_{it} to produce using the constant-returns-to-scale production function $A_t f(n_{it}, k_{it})$ where A_t is exogenous aggregate productivity. Firm i also posts vacancies v_{it} at flow cost γ per vacancy. Then, the firm's total operating costs are $X_{it} \equiv [w_t n_{it} + r_t k_{it} + \gamma v_{it}]$. A fraction $0 \leq \phi \leq 1$ of these costs must be paid in advance so that firms face a working capital constraint. Following Aliaga-Díaz and Olivero (2010), firms develop deep habits with monopolistically-competitive lenders indexed by j, which offer differentiated loan services that firms use to finance their working capital costs. The amount of liquidity services obtained from lenders by firm i is given by

$$x_{it} = \left[\int_0^1 (l_{ijt} - \omega s_{jt-1})^{\frac{\xi_t - 1}{\xi_t}} \, dj \right]^{\frac{\xi_t}{\xi_t - 1}}, \tag{12}$$

where

$$s_{jt-1} = \rho^s s_{jt-2} + (1 - \rho^s) l_{jt-1}, \tag{13}$$

and $l_{i,j,t}$ is firm i's demand for credit from lender j in period t, and ξ_t is the elasticity of substitution among loan varieties. Stochastic movements in ξ_t affect credit spreads directly and capture exogenous financial disturbances (see, for example, Airaudo and Olivero, 2018).

Intuitively, during downturns, loans become less substitutable because of a heightened perception of risk or an increase in asymmetric information relative to normal times. This is reflected in a lower ξ_t. Alternatively, fluctuations in ξ_t can embody changes in the substitutability between riskier (subprime) and less risky (regular) loans. Importantly, a reduction in this substitutability relative to trend contributes to the countercyclicality of credit spreads.

The case of $\omega > 0$ implies deep habits in credit markets: the firm's demand for credit depends on past borrowing. Then, the term $\omega s_{j,t-1}$ in $x_{i,t}$ captures the *borrower "hold-up" effect*, with ω measuring the extent of the hold-up. The term $s_{j,t-1}$ in equation (12) is defined as $s_{jt-1} \equiv \int_0^1 s_{i,j,t-1} di$, which corresponds to the beginning of period-t cross-sectional (across firms) average stock of accumulated past loans obtained from bank j. The stock of habits $s_{j,t-1}$ is characterized by the law of motion in equation (13). Specifically, it is a linear function of its value in the previous period and the average level of borrowing from lender j in $t-1$, $l_{j,t-1} \equiv \int_0^1 l_{i,j,t-1} di$.

We first find firm i's optimal relative demand for loans from lender j. Formally, firm i minimizes its total borrowing costs $\int_0^1 R^l_{j,t} l_{i,j,t} dj$ subject to equation (12), yielding firm i's optimal demand for loans issued by lender j, l_{ijt}, as a function of the relative loan rate charged by lender j and the stock of borrowing habits related to the same loan variety. Formally, this optimal demand is given by

$$l_{i,j,t} = \left(\frac{R^l_{j,t}}{R^l_t} \right)^{-\xi_t} x_{it} + \omega s_{j,t-1}, \tag{14}$$

where $R^l_t \equiv \left[\int_0^1 \left(R_{l,jt} \right)^{1-\xi_t} dj \right]^{\frac{1}{1-\xi_t}}$ is the aggregate loan rate index. As equation (14) states, l_{ijt} is higher the cheaper it is to borrow from lender j (i.e. the lower $\frac{R_{l,jt}}{R_{l,t}}$ is) and/or the stronger is the lender-borrower relationship (i.e. the larger ω and/or s_{jt-1} are).

In turn, each firm i chooses its demand for labor and capital as well as vacancy postings to maximize $E_0 \sum_{t=0}^{\infty} \Xi_{t|0} \pi_{i,t}$ subject to $\pi_{it} = \left[A_t f(n_{it}, k_{it}) + x_{i,t} - (1-\phi) X_{i,t} - \int_0^1 R^l_{j,t-1} l_{i,j,t-1} dj \right]$, the perceived evolution of employment

$$n_{it} = (1-\rho^n) n_{it-1} + v_{it} q(\theta_t), \tag{15}$$

and the amount of working capital $X_{it} \equiv [w_t n_{it} + r_t k_{it} + \gamma v_{it}]$, where $x_{i,t} = \phi X_{i,t}$, $\int_0^1 R^l_{j,t} l_{i,j,t} dj = R^l_t x_{i,t} + \Gamma_t$, $\Gamma_t \equiv \omega \int_0^1 R_{l,jt-1} l_{jt-1} dj$, and $q(\theta_t)$ denotes the job-filling probability.

Firm i's job creation condition is given by

$$\begin{aligned} \frac{\gamma\left[(1-\phi)+\phi E_t \Xi_{t+1|t} R^l_t\right]}{q(\theta_t)} &= A_t f_{n_i}(n_{it}, k_{it}) - w_t\left[(1-\phi)+\phi E_t \Xi_{t+1|t} R^l_t\right] \\ &\quad +(1-\rho^n) E_t \Xi_{t+1|t}\left[\frac{\gamma\left[(1-\phi)+\phi \Xi_{t+2|t+1} R^l_{t+1}\right]}{q(\theta_{t+1})}\right]. \end{aligned} \tag{16}$$

This condition equates the expected marginal cost of posting a vacancy to the expected marginal benefit. The latter is comprised of the marginal product of labor net of the real wage, adjusted for the fact that firms must pay a fraction of their wage and vacancy-posting bills in advance, and the continuation value of the employment relationship. In turn, the demand for capital by firm i is standard and given by $A_t f_{k_i}(n_{it}, k_{it}) = r_t\left[(1-\phi)+\phi E_t \Xi_{t+1|t} R^l_t\right]$. This condition equates the marginal benefit of a unit of capital to the marginal cost, where the latter also takes into account the firm's working capital constraint. For future reference, note that in a symmetric equilibrium, total output is $y_t = A_t f(n_t, k_t)$.

3.3 Matching and Wage Determination

The matching function $m(s_{ht}, v_t)$ is constant-returns-to-scale. The matching probabilities for household members and firms are $f(\theta_t) \equiv m(s_{ht}, v_t)/s_{ht}$ and $q(\theta_t) \equiv m(s_{ht}, v_t)/v_t$, respectively. Following the search literature, we assume bilateral Nash bargaining between households and firms, where the worker's bargaining power is $0 < \eta_n < 1$.

Appendix D shows that the Nash real wage can be expressed as

$$\begin{aligned} w_t &= \frac{\eta_n A_t f_n(n_t, k_t)}{\left[(1-\phi)+\phi E_t \Xi_{t+1|t} R^l_t\right]} + (1-\eta_n)\chi \\ &\quad +\eta_n(1-\rho^n) E_t \Xi_{t+1|t}\left[\frac{\gamma}{q(\theta_{t+1})}\left(\frac{\left[(1-\phi)+\phi E_{t+1} \Xi_{t+2|t+1} R^l_{t+1}\right]}{\left[(1-\phi)+\phi E_t \Xi_{t+1|t} R^l_t\right]} - [1-f(\theta_{t+1})]\right)\right]. \end{aligned} \tag{17}$$

This expression shows that credit market conditions affect how the surplus from employment relationships is shared, and will therefore affect (1) firms' incentives to post vacancies, and (2) household members' incentives to search for employment and therefore participate in the labor market. In particular, all else equal, an increase in R^l_t puts downward pressure on wages.

3.4 Lenders

There is a continuum of lenders indexed by j on the unit interval.[10] Each variety of loans is produced by a lender operating in a monopolistically-competitive loan market and in a perfectly-competitive deposits market.

Each period, lender j chooses its demand for deposits $d_{j,t}$ and the interest rate charged on loans $R^l_{j,t}$ to maximize $E_0 \sum_{t=0}^{\infty} \Xi_{t|0}\pi_{j,t}$ subject to the lender's cash flow

$$\pi_{j,t} = d_{j,t} - l_{j,t} + R^l_{j,t-1} l_{j,t-1} - R^d_{t-1} d_{j,t-1} - \kappa_t, \tag{18}$$

the balance sheet condition $l_{j,t} = d_{j,t}$, and lender j's aggregate demand for loans from firms

$$l_{j,t} \equiv \int_0^1 l_{i,j,t} di = \int_0^1 \left[\left(\frac{R^l_{j,t}}{R^l_t} \right)^{-\xi_t} x_{i,t} + \omega s_{j,t-1} \right] di. \tag{19}$$

where κ_t denotes the fixed cost of production (the presence of κ limits entry into the sector and ensures that profits are relatively small on average despite equilibrium price-cost margins being positive). R^d is the common risk-free interest rate on deposits paid by all lenders.

The first-order conditions with respect to $d_{j,t}$ and $R^l_{j,t}$ are

$$\Omega_{j,t} = E_t \Xi_{t+1|t} \left[(R^l_{j,t} - R^d_t) + \omega \Omega_{j,t+1} (1 - \rho^s) \right], \tag{20}$$

and

$$E_t \Xi_{t+1|t} l_{j,t} = -\Omega_{j,t} \frac{\partial l_{j,t}}{\partial R^l_{j,t}}, \tag{21}$$

[10] We follow the literature on banking frictions in the context of market power in banking and abstract from bank entry and exit (see Mandelman, 2010, Olivero, 2010, and Gertler and Kiyotaki, 2015, among others). Incorporating an endogenous measure of banks and sunk entry costs is beyond the scope of this paper, which focuses on labor market dynamics and the volatility of spreads. Allowing for procyclical bank entry, which is in line with the data, would introduce additional shock propagation by enhancing the countercyclicality of spreads, thereby strengthening the interaction between cyclical spread movements and labor force participation that ultimately contributes to matching the data well. More broadly, with endogenous bank entry, the underlying mechanisms of our model would remain unchanged.

respectively, where Ω_{jt} is lender j's shadow value of lending an extra unit of resources to a firm in period t.

The first condition states that the value of lending an extra unit in period t is comprised of the short-term returns from that operation $((R^l_{j,t} - R^d_t)E_t\Xi_{t+1|t})$ and the future expected profits associated with the fact that a share of this lending will be "held-up" in period $t+1$ as a result of deep habits in credit markets. The second condition states that the marginal revenue from increasing the lending rate (given by the discounted value of the loans, $l_{j,t}E_t\Xi_{t+1|t}$) must equal the marginal cost of doing so. This cost is given by the implied reduction in the quantity of loans demanded, $\frac{\partial l_{j,t}}{\partial R^l_{j,t}}$, evaluated at the shadow price $\Omega_{j,t}$.

Combining equations (20) and (21) and using the approximation $\frac{R^l_j}{R^d} \approx (1 + R^l_j - R^d)$ and imposing symmetry across banks, the credit spread can be expressed as

$$(R^l_t - R^d_t) = \left\{\xi_t \left[1 - \omega\rho^s \frac{s_{t-2}}{l_t} - \omega(1-\rho^s)\frac{l_{t-1}}{l_t}\right]\right\}^{-1} - \omega(1-\rho^s)\frac{E_t\Xi_{t+1|t}\Omega_{t+1}}{E_t\Xi_{t+1|t}}. \tag{22}$$

Two relevant features in this expression are worth noting. First, for a given value of ξ, the presence of deep habits ω and long-lasting lending relationships ρ^s imply that the credit spread is influenced by the stock of (current and past) loans—an endogenous object—which contributes to generating endogenous countercyclical credit spreads (see Aliaga-Díaz and Olivero, 2010a). Second, in the absence of deep habits (i.e., $\omega = 0$), an exogenous reduction in ξ—that is, an adverse financial shock—generates an increase in spreads (given this fact, shocks to ξ could be interpreted as mark-up shocks). To the extent that higher spreads raise firms' costs and reduce labor and capital demand, adverse financial shocks generate downturns, thereby contributing to the countercyclicality of spreads as well. Importantly for our purposes, given that ξ affects the credit spread directly, the volatility of financial shocks will have a direct effect on both the volatility *and* cyclicality of credit spreads. In particular, all else equal, the greater the change in ξ relative to trend, the greater the countercyclicality of spreads. Given these facts, it follows that in our model cyclical movements in credit spreads are affected by endogenous movements in loans as well as exogenous disturbances embodied in ξ, where the volatility of financial shocks directly influences the volatility and cyclicality of credit spreads.

Before closing the model, we note that the link between credit spreads and the length of lending relationships ρ^s can be positive or negative depending on the parameterization. As such, the model-implied equilibrium credit spread is not necessarily increasing in the length of relationships between lenders and firms. This model feature is broadly consistent with existing empirical evidence.[11]

3.5 Government and Market Clearing

Unemployment benefits are financed with lump-sum taxes. Then, the government budget constraint is $\chi(1-f(\theta_t))s_{ht} = T_t$. Combining the government budget constraint, the household budget constraint, firm profits, and bank profits and imposing symmetric equilibrium yields the economy's resource constraint: $y_t = c_t + inv_t + \gamma v_t$.

4 Quantitative Analysis

Functional Forms and Shock Processes We adopt standard functional forms in the literature: $u(c_t) = \ln c_t$ and $h(lfp_t) = [\psi/(1+1/\iota)]\, lfp_t^{1+\frac{1}{\iota}}$, where $\iota > 0$ (Arseneau and Chugh, 2012). The production and matching functions are Cobb-Douglas: $f(n_t, k_t) = A_t n_t^{1-\alpha} k_t^{\alpha}$ and $m(s_{ht}, v_t) = M s_{ht}^{\mu} v_t^{1-\mu}$, where $0 < \alpha, 0 < \mu < 1$ and M is exogenous matching efficiency. Aggregate productivity A_t and the elasticity of substitution among loans follow independent AR(1) processes in logs with means A and ξ, autocorrelation coefficients $0 < \rho_A, \rho_\xi < 1$, and shocks $\varepsilon_t^A \sim N(0, \sigma_A)$, $\varepsilon_t^\xi \sim N(0, \sigma_\xi)$, where σ_ξ dictates the volatility of financial shocks.

[11] Some studies document that spreads are increasing in the duration of relationships and interpret this result as evidence that lenders accumulate private information on their borrowers over the course of the relationship, which generates a lock-in problem and ultimately allows banks to exploit informational rents through higher spreads (Petersen and Rajan, 1994). Other studies find that spreads fall for longer relationships and interpret this result as bank costs falling over the course of the relationship, and lenders sharing the resulting efficiency gains with their customers (Berger and Udell, 1995; Schenone, 2009). Existing theoretical work also predicts a non-monotonic link between spreads and borrower-lender relationship duration. Greenbaum et al. (1989), Sharpe (1990), Rajan (1992) and vonThaden (2004) focus on the lock-in story and predict a positive relationship. Boot and Thakor (1994) model the efficiency-gains-sharing story and predict an inverse relationship.

Parameters from Literature A period is a quarter. We follow the DSGE and labor search literatures and set the capital share $\alpha = 0.34$, the subjective discount factor $\beta = 0.99$, and the capital depreciation rate $\delta = 0.025$. The job separation probability is $\rho_n = 0.10$ (Arseneau and Chugh, 2012). We set the matching elasticity and Nash bargaining power parameters so that $\mu = 0.4$ and $\eta_n = 0.5$, respectively (Petrongolo and Pissarides, 2001).[12] Following related literature on financial frictions (Chugh, 2013; Iacoviello, 2015; Garín, 2015), we set the working capital parameter $\phi = 1$. Similarly, we normalize $A = 1$ and set $\rho_A = 0.95$, $\sigma_A = 0.007$, which are standard values for aggregate productivity shocks in the RBC literature. Turning to the parameters pertaining to credit markets, we set $\rho_s = 0.50$ and $\rho_\xi = 0.90$ as a baseline only, where the high persistence of financial shocks is consistent with related studies on financial frictions (see, for example, Iacoviello, 2015, or Garín, 2015). Table A5 in Appendix E confirms that our quantitative findings are robust to alternative values for ρ_s and ρ_ξ. Finally, Aliaga-Díaz and Olivero (2010a) use data on BAA spreads in an RBC model with deep habits in credit markets and estimate a value of $\omega = 0.72$. Given our interest in the role of endogenous participation in amplifying financial shocks and, importantly, in the interaction between endogenous participation and deep habits in credit markets amid these shocks, we set $\omega = 0.72$ as a baseline. Then, given this baseline, we study how cyclical labor market dynamics change as we vary ω. This exercise allows us to highlight the role of deep habits in the presence of endogenous LFP in a transparent way.

Calibrated Parameters We calibrate the remaining parameters χ, M, γ, ψ, ι, ξ, and σ_ξ to match the following targets based on U.S. data over the period spanning 1987Q1-2017Q4 (as in Section 2): an average unemployment-benefit replacement rate of 50 percent; mean job-finding and job-filling probabilities equal to 0.60 and 0.70, respectively; a mean labor force participation (LFP) rate of 0.657; a relative volatility of LFP of 0.171, a mean credit spread inclusive of switching costs of 0.1733, and a relative cyclical volatility of credit spreads of 28.17. Targeting the volatilities of credit spreads and LFP allows us to assess the extent to which these two features play a quantitative role in labor market volatility. The resulting parameter values are $\chi = 0.8365$, $M = 0.6581$, $\gamma = 0.9098$, $\psi = 63981.9$, $\iota = 0.0384$,

[12]Related studies on financial frictions and labor markets also adopt calibrations that deviate from the Hosios condition in the labor market (see, for example, Petrosky-Nadeau, 2014, and Garín, 2015).

$\xi = 15.6961$, and $\sigma_\xi = 0.2085$. The parameter values we adopt from existing literature, the calibrated parameters, and their corresponding targets are summarized in Table 2.[13]

4.1 Business Cycle Statistics

We use data from 1987Q1 to 2017Q4 for real GDP, private consumption, investment, vacancies, the unemployment and labor force participation (LFP) rates, and credit spreads and compare selected second moments generated by our benchmark model to their empirical counterparts.

Baseline Business Cycle Statistics: Data vs. Model Table 3 shows that the benchmark model can quantitatively replicate a number of non-targeted second moments in the data well. In particular, under a calibration strategy that replicates the volatility of credit spreads and LFP, the model generates highly volatile vacancies and unemployment and strongly countercyclical unemployment that are very close to the corresponding moments in the data, as well as factual procyclical consumption, investment, and vacancies. Moreover, our model successfully generates factual procyclical fluctuations in LFP and a strongly countercyclical credit spread, with the latter being close to its empirical counterpart. For completeness, Table A11 in Appendix E compares lags and leads of select variables with GDP in the data to the same moments in the benchmark model and confirms that the model does well in replicating these additional features of the data.

To highlight the relevance of the benchmark model's most important elements, Table 3 shows variants of the benchmark model when we shut down: (1) financial shocks or (2) deep habits in credit markets. In addition, to stress the relevance of endogenous LFP, the table shows results from a version of the benchmark model with constant (and exogenous) LFP as well as variants of this simpler model without financial shocks and without deep habits. For comparability across models, each of these benchmark-model variants is cali-

[13]We note that our baseline calibration also yields the following *non-targeted first-moments*: a steady-state (or average) unemployment rate of 6.25 percent, broadly in line with the 6 percent in the data for the time period we consider; a steady-state (or average) consumption-output ratio of 0.718, which is close to its empirical counterpart of 0.66; and a steady-state (or average) investment-output ratio of 0.242, which is close to its empirical counterpart of 0.173.

Preference and Production Parameters			
Discount factor β	0.99	Steady-State TFP $\bar{A}$	1
Persistence of TFP shocks ρ_A	0.95	Volatility of TFP shocks σ_A	0.007
Capital share α	0.34	Depreciation rate δ	0.025
Labor and Credit Market Parameters			
Matching elasticity μ	0.4	Bargaining power η_n	0.5
Job separation probability ρ_n	0.10	Working capital Share ϕ	1
Persistence of lending relationships ρ_s	0.5	Deep-habits parameter ω	0.72
Persistence of financial shocks	0.90		

Calibrated Parameters (Left) and Calibration Targets (Right)			
Disutility of LFP Param. ψ	63982	Average LFP	0.657
Elasticity of LFP ι	0.0384	$\sigma_{lfp_t}/\sigma_{GDP_t}$	0.171
Unemployment benefits χ	0.8365	χ/w	0.50
Matching Efficiency M	0.6581	Job-finding probability	0.60
Marginal cost of posting vacancies γ	0.9098	Job-filling probability	0.70
Elasticity of substitution of bank loans ξ	15.6961	Spread incl. switching costs	0.1733
Volatility of financial shocks σ_ξ	0.2085	σ_{spread_t}	28.17

Table 2: Parameters from Literature, Calibrated Parameters, and Calibration Targets

Targeted Moments	Data	Benchmark Model	Benchmark, No Fin. Shocks	Benchmark, $\omega = 0$	Benchmark, No Fin. Shocks, $\omega = 0$	Constant LFP	Constant LFP, No Fin. Shocks	Constant LFP, $\omega = 0$	Constant LFP, No Fin. Shocks, $\omega = 0$
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.171	0.171	-	-	-	-
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	4.437	28.17	0.032*	28.17	4.133	28.17	0.032*
Non-Targeted Moments									
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.332	0.322	0.346	0.333	0.348	0.339	0.357
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	2.937	2.865	2.951	2.871	2.932	2.882	2.955
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	2.844	10.819	1.971	3.742	1.068	3.848	0.813
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	3.741	7.967	2.019	4.120	1.267	4.006	0.831
$corr(c_t, y_t)$	0.898	0.806	0.899	0.823	0.922	0.844	0.918	0.851	0.929
$corr(inv_t, y_t)$	0.899	0.922	0.985	0.939	0.993	0.947	0.992	0.953	0.993
$corr(ur_t, y_t)$	-0.856	-0.716	-0.958	-0.676	-0.813	-0.482	-0.715	-0.474	-0.685
$corr(v_t, y_t)$	0.881	0.504	0.563	0.494	0.760	0.603	0.908	0.573	0.999
$corr(lfp_t, y_t)$	0.332	0.636	0.780	0.603	0.959	-	-	-	-
$corr(spread_t, y_t)$	-0.664	-0.563	-0.553	-0.522	0.961	-0.452	-0.545	-0.413	0.962

Notes: Empirical second moments based on HP-filtered data with smoothing parameter 1600. * denotes a non-targeted moment.

Table 3: Business Cycle Statistics - Data vs. Benchmark Model and Model Variants

brated to match the same targets across models whenever appropriate.[14] Comparison of the benchmark model to these variants highlights the relevance of endogenous LFP *alongside* financial shocks in producing quantitatively-factual cyclical labor market and aggregate dynamics: the benchmark model can replicate virtually all of the volatility of unemployment and vacancies in the data, whereas the model with constant LFP or without financial shocks cannot.

Abstracting from financial shocks in the benchmark model implies that spreads, unemployment, and vacancies are considerably less volatile compared to both the benchmark model with financial shocks and the data. This occurs even as spreads exhibit the same degree of countercyclicality in the two model versions. In turn, abstracting from deep habits in credit markets (i.e., setting $\omega = 0$) in the benchmark model reduces the countercyclicality of spreads and volatility of vacancies slightly compared to the benchmark model with deep habits (of note, per equations 12 and 13 in section 3.2, setting $\omega = 0$ implies that the length of credit relationships ρ^s becomes irrelevant as a factor that shapes cyclical dynamics since ρ^s affects volatility via ω). However, unemployment continues to be similarly volatile. The reason for this outcome is simple: as we noted in the discussion of the model's credit spread in equation 22, even in the absence of deep habits, spreads will be countercyclical (and volatile) *as long as there are financial shocks.* To the extent that we match the volatility of spreads *absent deep habits*, it follows that in equilibrium, vacancies will continue to be highly volatile amid financial shocks and endogenous LFP, which ultimately translates into highly volatile unemployment. To see this more clearly, Table 3 shows a version of the benchmark model where we shut down *both* deep habits *and* financial shocks: in this case, spreads become strongly *pro*cyclical, and the volatility of spreads (which is no longer a targeted moment in the absence of financial shocks), vacancies, and unemployment all drop dramatically compared to both the benchmark model and the data.

More crucially for our message, abstracting from endogenous LFP implies that such

[14]Without loss of generality and following the search and matching literature, the benchmark-model variant with constant LFP normalizes participation to one. Note that in the model variants without financial shocks, $\sigma_{spread_t}/\sigma_{y_t}$ is no longer a target since our original calibration used the volatility of financial shocks to match this second moment and we shut down those shocks. Similarly, in the benchmark-model variants with constant LFP, $\sigma_{lfp_t}/\sigma_{y_t}$ is no longer a target since LFP is constant in those model variants. For completeness, Table A12 in Appendix E presents the lags and leads of the model variant with constant LFP and compares them to the data.

model only captures slightly more than one third of the volatility of unemployment and less than half of the volatility of vacancies in the data (and therefore in our benchmark model). Moreover, this simpler model also generates a lower countercyclicality of unemployment relative to both the benchmark model and the data. The results from a model with constant LFP are broadly consistent with those in Garín (2015), whose framework also abstracts from modeling LFP. Unsurprisingly, a model with constant LFP and no financial shocks or no deep habits faces similar limitations in matching the data. All told, the results in Table 3 suggests the following: (1) LFP is an important amplification mechanism of financial shocks; (2) the *magnitude* of the volatility of spreads is critical for LFP to act as a *quantitatively-relevant* amplification mechanism; and (3) the countercyclicality of spreads is important for the degree of amplification, with a lower countercyclicality dampening the amplification effects of LFP. For completeness, Table A4 in Appendix E shows a version of Table 3 where we keep the baseline parameterization in the benchmark model and simply shut down financial shocks or deep habits without recalibrating the model to match the volatility of LFP and spreads. Our findings remain unchanged.

Robustness in Benchmark Model and Additional Results Before discussing the economic mechanisms of our model, we conduct a series of robustness experiments in our benchmark framework. Specifically, Tables A5, A6, A7, A8, and A10 in Appendix E show the following results. First, the benchmark model's ability to capture key facts in the data is robust to alternative values for the length of credit relationships ρ_s, the degree of deep habits ω, the persistence of financial shocks ρ_ξ, and the bargaining power of workers η_n. Second, the benchmark model's results remain unchanged under the Hosios condition. Third, the benchmark model generates virtually identical labor market dynamics to those in Table 3 if, instead of introducing financial shocks via fluctuations in ξ, these shocks enter via exogenous fluctuations in the degree of deep habits ω. A similar claim holds if we abstract from endogenous spreads and instead adopt a simplified environment that features an exogenous, countercyclical process for spreads that replicates the volatility of spreads in the data. Fourth, the benchmark model performs equally well amid factual cyclical movements in job separations, when these movements are shaped by fluctuations in credit spreads. Finally, we note that as shown in Table A5 in Appendix E, the inclusion of the wage bill in the working capital constraint plays an important role in generating high unemployment and job-vacancy volatility. This result is intuitive since wages are a key variable that affects firms' incentives to post vacancies, which in turn shape unemployment dynamics. Finally, Table A14 in Appendix E shows results from running the same VAR in Section 2 using the benchmark model's simulated data, and conducting Granger causality tests. The results in Table A14 are consistent with their empirical counterparts in Table A3 in Appendix C.

4.2 Endogenous Participation as an Amplification Mechanism of Financial Shocks

To understand how endogenous LFP amplifies financial shocks, Figure 3 compares the benchmark model and a version of our model with constant LFP by plotting normalized impulse response functions to an adverse financial shock.[15]

Across the two models, output, consumption, investment, wages and vacancies all fall, while unemployment and credit spreads rise. In the benchmark model, LFP falls. The behavior of unemployment and LFP is consistent with the VAR evidence from Section 2. Importantly though, the responses of the model with constant LFP are considerably more subdued, *even if the rise in credit spreads is for all intents and purposes identical in the two models*. To better understand the mechanisms behind this result, note that the adverse financial shock initially manifests itself in an increase in credit spreads, which raises firms' costs of labor, capital, and vacancies and pushes firms to reduce vacancies. *All else equal*, the initial contraction in vacancies puts downward pressure on wages. This fact is apparent by looking at in the real wage expression in equation (18).

[15]For completeness, the response to an adverse aggregate productivity shock in these two models is presented in Figure A2 in Appendix F.

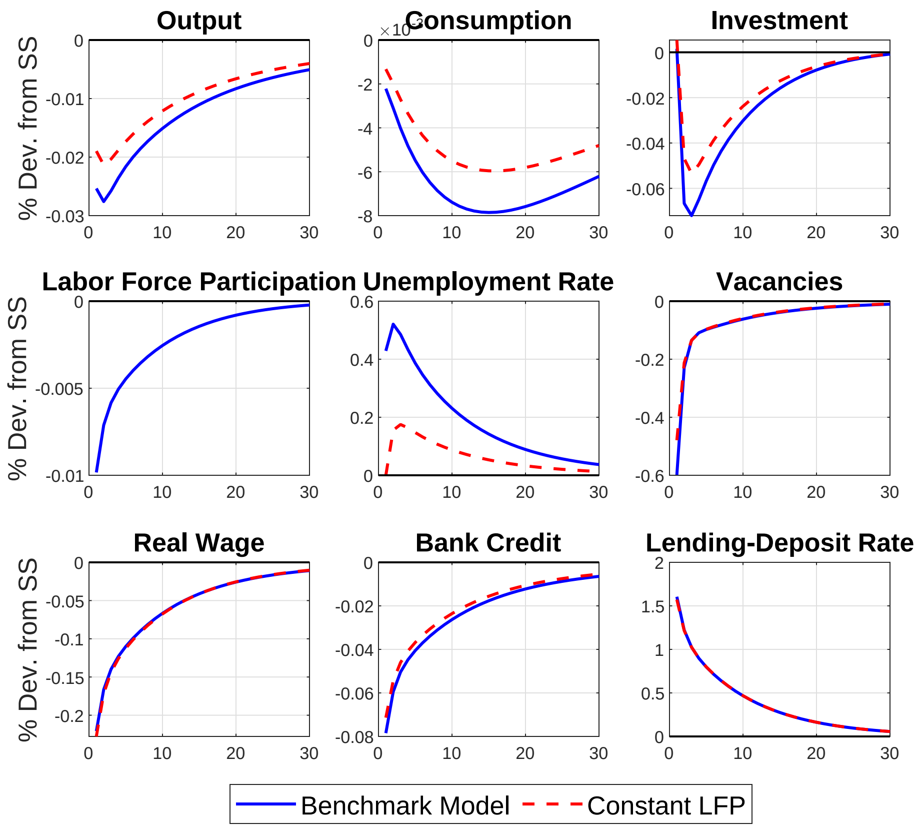
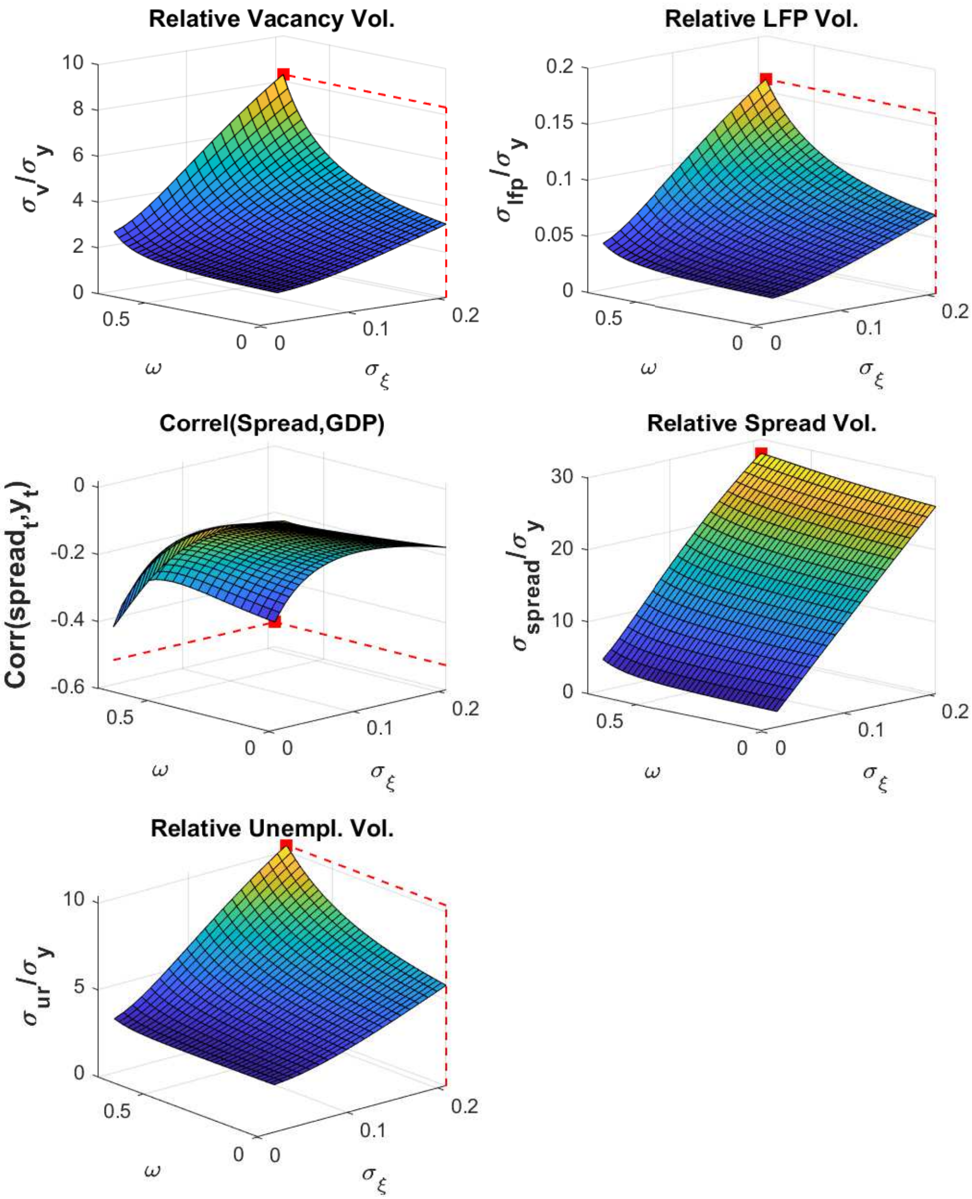


Figure 3: Response to a One-Standard-Deviation Adverse Financial Shock (Quarters after Shock)–The Role of Endogenous Labor Force Participation (Normalized Impulse Response Functions)

Critically, with endogenous LFP, this downward wage pressure lowers the marginal benefit of participation (recall equation (11)), which pushes households to reduce their measure of searchers, thereby generating a contraction in LFP. All else equal, this reduction in LFP has the opposite effect on wages relative to the reduction in vacancies, effectively exerting *upward* pressure on wages (this occurs via the job-filling probability, which is increasing in the measure of searchers for a given level of vacancies). Then, in response to the behavior of LFP and the resulting reduction in the pool of potential workers that firms can draw potential workers from, firms reduce vacancies by even more such that, in equilibrium, vacancies fall by more relative to an environment with constant LFP. Recall that the unemployment rate in the benchmark model is $ur_t = [1 - f(\theta_t)]\, s_{ht}/lfp_t$. Then, relative to an economy with constant LFP, the combination of a larger equilibrium drop in vacancies and LFP (and ultimately market tightness) implies that the term $\left[(1-f(\theta_t))\right]/lfp_t$ rises by more. Despite the fact that searching is less attractive and therefore s_{ht} is lower, the rise in $\left[(1-f(\theta_t))\right]/lfp_t$ dominates quantitatively, ultimately leading to a much sharper increase in the *equilibrium* unemployment rate.

Labor Market Fluctuations, Spread Volatility, and Deep Habits Having established how LFP amplifies financial shocks relative to a standard environment with constant LFP, we turn to the factors that shape *the strength* with which LFP amplifies these shocks, mainly the volatility of spreads and deep habits in credit markets. We do so in two steps. First, focusing on the benchmark model *only*, we lower the volatility of financial shocks (σ_ξ) and the degree of deep habits (ω) from their baseline values down to zero, holding all other parameters at their baseline values. Second, we perform a similar experiment for σ_ξ and ω separately, comparing the benchmark model to its variant with constant LFP.

Figure 4 plots the relationship between the relative volatility of vacancies, LFP, and unemployment, as well as the cyclical correlation between credit spreads and output, for different combinations of the volatility of financial shocks σ_ξ and the degree of deep habits ω in our benchmark model. The figure illustrates the following results. Lowering ω for a given value of σ_ξ reduces the relative volatility of vacancies, LFP, and unemployment while making spreads less countercyclical, but has marginal effects on the volatility of spreads. While lowering σ_ξ for a given value of ω also reduces the volatility of vacancies, LFP, and unemployment and makes spreads less countercyclical, in contrast to lowering ω, we observe a sharp decline in the volatility of spreads. Critically, the countercyclicality of spreads, by itself, is not associated with highly volatile unemployment and vacancies (consider, for example, the benchmark-model outcome, which is characterized by strongly countercyclical and volatile spreads, against a case of the model with a low σ_ξ and a high ω, which generates strongly countercyclical spreads but low spread volatility. This last model produces much lower vacancy and unemployment volatility).



Notes: The red square marks the value of the corresponding second moment generated by the benchmark model under the baseline calibration.

Figure 4: Benchmark Model: Deep Habits in Credit Markets, Credit-Spread Volatility, and Labor Market Fluctuations

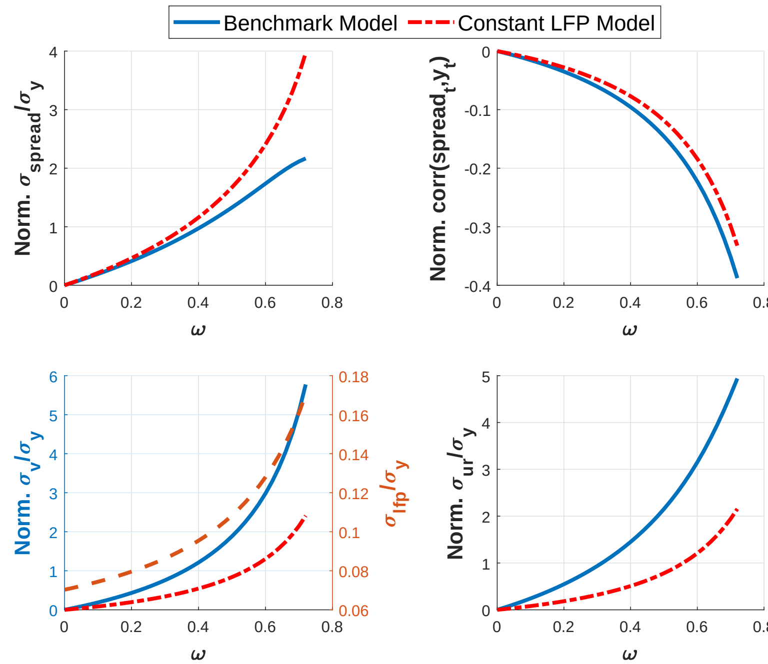


Figure 5: Deep Habits and Unemployment and Vacancy Volatility: Benchmark Model vs. Exogenous Participation

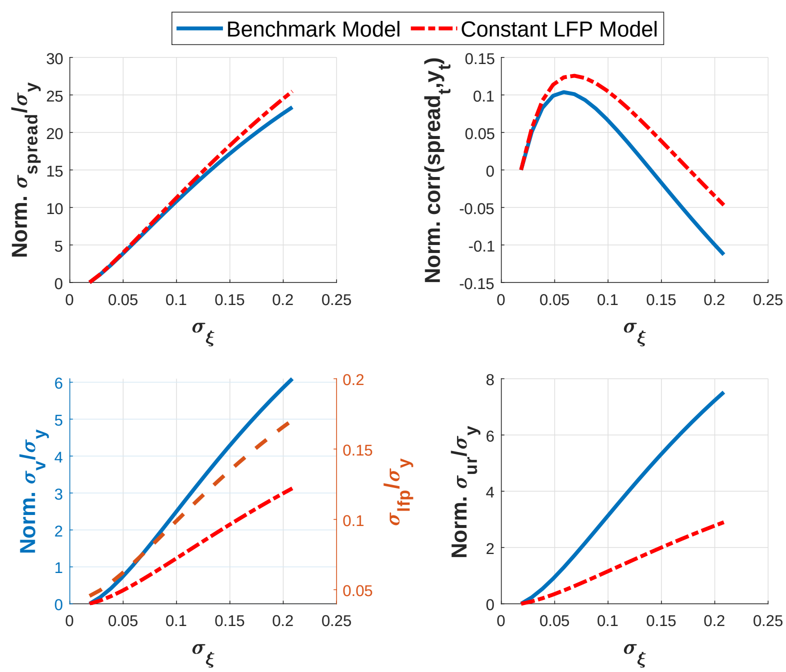


Figure 6: Financial Shocks and Unemployment and Vacancy Volatility: Benchmark Model vs. Exogenous Participation

With these results in mind, we now compare the changes in the relative volatility of spreads, unemployment, and vacancies in our benchmark model and in a version of the model with constant LFP as we individually change ω and σ_ξ. Figure 5 shows the case for ω, *holding all other parameters (including* σ_ξ*) at their baseline values*, while Figure 6 shows the case for σ_ξ, *holding all other parameters (including* ω*) at their baseline values.* Of note, for ease of comparison between models, the second moments in the models without deep habits ($\omega = 0$) and without financial shocks ($\sigma_\xi = 0$) are normalized to zero. Then, the changes in the second moments as we increase ω or σ_ξ, which are presented in the two figures, can be interpreted as changes in those second moments *relative* to scenarios without deep habits or without financial shocks, respectively, in a straightforward way.

Consider a gradual increase in ω from zero to its baseline value in the benchmark-model calibration (Figure 5). As ω increases, the relative volatility of spreads becomes greater and spreads become more countercyclical.[16] While the increase in the countercyclicality of spreads is similar across models, the increase in the volatility of spreads is, in relative terms, greater under constant LFP compared to the benchmark model. However, the increase in the volatility of vacancies and unemployment is greater *in the benchmark model*, and the differences in volatility across the two models become starker the greater ω is. Intuitively, a greater ω implies that financial frictions, which are embodied in credit spreads, become more influenced by firms' and lenders' decisions over credit (recall equation (22)), which leads to more volatile spreads for a given set of shocks. The reason why the volatility of unemployment rises faster in the benchmark model, even amid a more gradual increase in the volatility of spreads, is as follows. As spreads become more volatile amid a greater ω, firms' vacancy-posting decisions become more sensitive to shocks, which in turn makes households' participation decisions more sensitive as well, ultimately resulting in both greater job-vacancy volatility and greater LFP volatility. The feedback effect between vacancies and LFP is of course absent in a model with constant LFP, thereby limiting the impact of a greater ω on the volatility of vacancies and unemployment relative to the benchmark model.

Now consider a gradual increase in σ_ξ from zero to its baseline value in the benchmark-

[16]Note that a negative number for the *normalized* cyclical correlation between spreads and output means that spreads are more countercylical *relative* to the model under $\omega = 0$.

model calibration (Figure 6). As σ_ξ increases, the volatility patterns are qualitatively similar to those we just described for the case of ω, with the change in the volatility of spreads across models being fairly similar over the σ_ξ range. Intuitively, with an additional margin of adjustment in the labor market—mainly LFP—the more volatile are financial shocks, the more variable LFP becomes, which feeds into the volatility of vacancies and ultimately unemployment. Once again, the feedback effect between LFP and vacancies, which strengthens with σ_ξ, is absent in a model with constant LFP.[17]

All told, Figures 5 and 6 show how, as ω and σ_ξ are gradually raised from zero to their baseline values, endogenous LFP amplifies the cyclical behavior of vacancies and unemployment relative to an environment with constant LFP.

Hosios Condition and Hagedorn-Manovskii Calibration Table A8 in Appendix E shows that our benchmark model's findings and conclusions remain unchanged if we adopt a Hosios-type calibration where the matching elasticity μ is equal to the workers' bargaining power η_n.[18] In addition, the same table presents results for the benchmark model under a calibration in the spirit of Hagedorn and Manovskii (2008) (HM). In particular, this calibration entails adopting a very low bargaining power for workers η_n alongside a value of unemployment benefits χ that is very close to the steady-state wage (see Appendix E for more details). Under the HM-type calibration, the relative volatilities of vacancies and unemployment are even higher compared to the volatility under our baseline calibration, and therefore higher than in the data; this is not surprising since the benchmark model is already able to generate most of the labor market volatility in the data conditional on matching the volatility of spreads and LFP. However, *amid a spread volatility that is consistent with the data*, the higher labor market volatility under the HM-type calibration comes at a cost of

[17]A third potential factor that could influence labor market volatility amid financial frictions rooted in deep habits is the length of credit relationships ρ^s. Changing ρ^s for a given value of ω generates marginal differences in unemployment volatility between our benchmark model and its constant-LFP counterpart, confirming the relative importance of ω and σ_ξ.

[18]For completeness, Appendix E shows results for two popular parameterizations in the literature: $\mu = \eta_n = 0.5$ and $\mu = \eta_n = 0.4$. Of note, amid financial frictions rooted in deep habits, setting $\mu = \eta_n$ may not guarantee efficiency in the labor market. Since our work does not explicitly revolve around efficiency, we leave the formal derivation of the constrained-efficient allocation amid labor search frictions and deep habits in credit markets for future work. Given these facts, the exercise in Table A8 should be interpreted as a robustness check and not as an exercise that replicates efficient allocations in our model. We thank an anonymous associated editor for pointing this out.

having countercyclical investment and consumption, which is at odds with the data. Of note, this only occurs in the presence of financial shocks, which our analysis showed are important to match the empirical volatility of spreads.[19] More broadly, this experiment suggests that a framework that replicates the empirical volatility of spreads and LFP can reasonably match the volatility of the labor market in the data, while also generating consistent macroeconomic dynamics, under a low contemporaneous value of unemployment. As such, our results are related to Shimer (2005), HM (2008), Eckstein et al. (2019), and others who have highlighted the empirical volatility of unemployment and vacancies and studied the conditions under which search models can quantitatively replicate the data, either in conventional search models or models enriched to have other frictions.

5 Conclusions

In the U.S., credit spreads are positively correlated with unemployment but also negatively correlated with labor force participation. We introduce borrower-lender relationships via deep habits into a general equilibrium search model with endogenous labor force participation to shed light on the role of labor force participation as an amplification channel of financial shocks in the labor market. Under quantitatively-factual cyclical credit-spread and labor-force-participation dynamics driven by aggregate productivity and financial shocks, the model generates highly volatile unemployment and vacancies, as well as factual aggregate fluctuations. Endogenous participation plays a central role in amplifying the effects of countercyclical and volatile spreads on labor market dynamics. More broadly, our work stresses the relevance of supply-side labor market factors, which have received less attention in the literature, as an important channel that amplifies the response of the labor market to financial shocks.

[19] Intuitively, under the HM-type calibration and amid a downturn induced by an adverse financial shock, the total resource cost of posting vacancies drops dramatically as a result of a significant drop in vacancies that is magnified by the high contemporaneous value of unemployment that characterizes the HM calibration. The sharp fall in the total cost of vacancy postings frees up resources for consumption and investment even as output contracts, making consumption and investment countercyclical. Table A9 also shows that adopting a lower worker bargaining power under a conventional contemporaneous value for unemployment (as in the benchmark model) continues to generate high labor market volatility but reduces the procyclicality of consumption and investment relative to both the benchmark model under the baseline calibration and the data.

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A Data Details

Section 2 uses several macroeconomic, financial, and labor-market time series for the period 1987Q1-2017Q4 to present a set of stylized facts on the link between credit spreads and unemployment, vacancies, and labor force participation over the business cycle. Job vacancies are obtained from Regis Barnichon (https://sites.google.com/site/regisbarnichon/data), and follow the methodology described in Barnichon (2010). The remaining time series are obtained from the Saint Louis Fed FRED database:

1. Real GDP (Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate)

2. Real investment (Real Gross Private Domestic Investment, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate)

3. Real private consumption (Real Personal Consumption Expenditures, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate)

4. Unemployment rate (Civilian Unemployment Rate, Percent, Quarterly, Seasonally Adjusted)

5. Labor force participation (Civilian Labor Force Participation Rate, Percent, Quarterly, Seasonally Adjusted)

6. Credit spread (Moody's Seasoned BAA Corporate Bond Minus Federal Funds Rate, Percent, Quarterly, Not Seasonally Adjusted; we obtain the seasonally-adjusted series using the Census X-12 methodology)

B Business Cycle Statistics: Alternative Detrending Methodologies

Table A1: Cyclical Correlations between Labor-Market Measures and Credit Spreads (1987Q1-2017Q4), Butterworth (BW) and Christiano-Fitzgerald (CF) Detrending Methodologies

	Unempl. Rate	**Part. Rate**	**Vacancies**
BW-Filtered			
Credit Spread	0.5519*	-0.2668*	-0.5569*
	(0.0000)	(0.0000)	(0.0000)
CF-Filtered			
Credit Spread	0.4307*	-0.2565*	-0.3953*
	(0.0000)	(0.0000)	(0.0000)

Sources: Saint Louis FRED Database and Barnichon (2010). Notes: Unempl. Rate is the civilian unemployment rate and Part. Rate is the labor force participation rate. Vacancies are measured by job openings as in Barnichon (2010). BW and CF denote the Butterworth and Christiano-Fitzgerald filters, respectively. P-values in parentheses. A * denotes significance at the 5 percent level.

Table A2: Cyclical Correlations: Leads and Lags of Credit Spreads with Unemployment Rate, Participation Rate, and Vacancies

	Unemployment Rate			
	HP	**BK**	**BW**	**CF**
Spread$_t$	0.5823*	0.5971*	0.5519*	0.4307*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-1}$	0.5352*	0.5609*	0.5065*	0.4065*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-2}$	0.4254*	0.4596*	0.3928*	0.3212*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-3}$	0.2809*	0.3149*	0.2424*	0.1940*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-4}$	0.1470*	0.1586*	0.1073	0.0554
	(0.0000)	(0.0000)	0.0001	0.0021
	Participation Rate			
	HP	**BK**	**BW**	**CF**
Spread$_t$	-0.3092*	-0.3179*	-0.2668*	-0.2565*
	(0.0000)	(0.0002)	(0.0005)	(0.0004)
Spread$_{t-1}$	-0.3712*	-0.3786*	-0.3302*	-0.3039*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-2}$	-0.3664*	-0.4062*	-0.3221*	-0.3113*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-3}$	-0.3593*	-0.3952*	-0.3145*	-0.2808*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-4}$	-0.3352*	-0.3483*	-0.2914*	-0.2227*
0	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Vacancies			
	HP	**BK**	**BW**	**CF**
Spread$_t$	-0.5987*	-0.7181*	-0.5569*	-0.3953*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-1}$	-0.5490*	-0.7088*	-0.5113*	-0.3730*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-2}$	-0.4660*	-0.6335*	-0.4326*	-0.2994*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spread$_{t-3}$	-0.3251*	-0.4752*	-0.2891*	-0.1880*
	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Spread$_{t-4}$	-0.1794*	-0.3228*	-0.1422	-0.0626
	(0.0001)	(0.0000)	(0.0004)	(0.0221)

Sources: Saint Louis FRED and Barnichon (2010). Notes: HP, BK, BW, and CF denote the Hodrick-Prescott, Baxter-King, Butterworth and Christiano-Fitzgerald filters, respectively. P-values in parentheses. A * denotes significance at the 5 percent level.

C Structural VAR Evidence: Additional Details

C.0.1 Granger Causality Tests

We conduct Granger causality tests to formally confirm that cyclical changes in credit markets as measured by shocks to the credit spread lead changes in labor markets. We use four lags, which is the optimal number of lags based on standard (AIC and HQ) lag criteria. Table A3 below shows that we can reject the null hypothesis that conditional on lagged values of the dependent variables, a set of four lags of the credit spread do not Granger-cause the unemployment rate, vacancies, or the labor force participation rate.

VAR Equation	**Excluded Variable**	χ^2	DF	Prob. $> \chi^2$
Unemployment Rate	Spread	8.5521	4	0.073
Vacancies	Spread	14.075	4	0.007
Labor Force Participation Rate	Spread	8.8111	4	0.066

Table A3: Granger Causality Test: Baseline Structural VAR

C.0.2 VAR Forecast Errors: Details

We follow den Haan (2000) and characterize the comovement between the unemployment rate, the labor force participation rate, vacancies, and spreads at business cycle frequencies by considering the correlation of VAR forecast errors at various horizons (quarters). To do so, we adopt the approach in den Haan (2000) and estimate the following VAR:

$$X_t = \alpha + \mu t + \sum_{l=1}^{4} \beta_l X_{t-l} + \sum_{i=1}^{3} \theta_i Q_{i,t} + \epsilon_t, \tag{23}$$

where X_t is a vector of endogenous variables that includes real GDP growth, the credit spread, the unemployment rate, the labor force participation rate, or vacancies (depending on which labor market variable we are interested in). The Q matrix includes quarterly dummy variables to control for seasonality. Similar to the estimation of the baseline VAR in the main text, we also use four lags (our findings remain unchanged under other commonly-adopted alternative number of lags consistent with quarterly data).

Based on the VAR estimates, we compute the k-period-ahead forecast of the variables,

$E_t X_{t+k}$, and obtain the k-period-ahead forecast errors, $X^{ue}_{t+k,t}$, as $X^{ue}_{t+k,t} \equiv X_{t+k,t} - E_t X_{t+k}$ and their variance-covariance matrix as a function of the coefficients β and $Var\left(\epsilon\right)$. Then, we compute $corr(k)$, which is the correlation coefficient between the k-period-ahead forecast errors of the two random variables in X: credit spreads and either the unemployment rate, the labor force participation rate, or vacancies. We construct 10-percent confidence bands for $corr(k)$ based on 2500 replications of the system. Figure 2 in the main text shows the correlations of the forecast errors of the credit spread with the corresponding forecast errors of each of our labor market variables of interest for various time horizons.

C.0.3 Structural VAR: Alternative Identification Assumptions

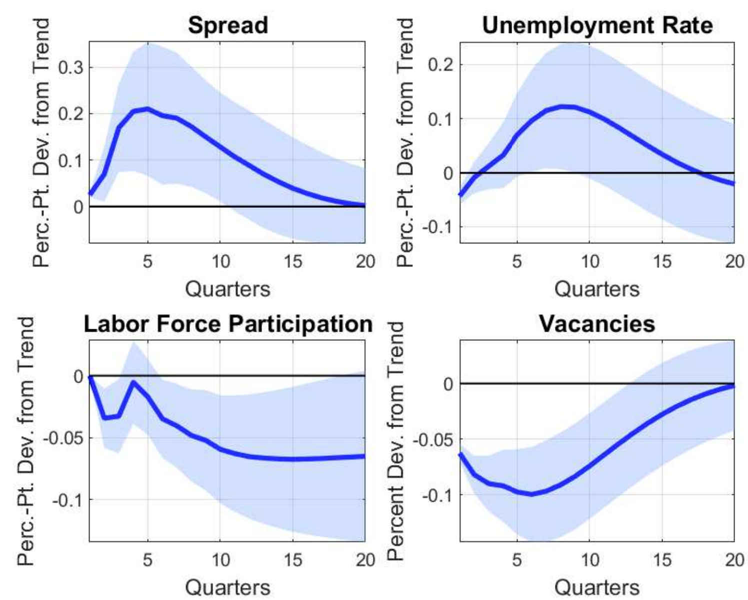

Figure A1: Response of Unemployment Rate, Labor Force Participation Rate, and Vacancies to a One-Percentage-Point Increase in Credit Spreads, Alternative Identification Restrictions

D Derivation of Nash Wage

For expositional clarity, we abstract from firm-specific subscripts. Let

$$\mathbf{J}_t \equiv \frac{\gamma\left[(1-\phi)+\phi E_t \Xi_{t+1|t} R^l_t\right]}{q(\theta_t)}$$

and

$$\mathbf{M}_t \equiv \frac{h'(lfp_t) - u'(c_t)\chi}{u'(c_t)f(\theta_t)}$$

denote the marginal value of employment for the firm and the household, respectively (see Arseneau and Chugh, 2012). Then, it is easy to show that the Nash wage is implicitly given by the surplus sharing rule

$$\mathbf{M}_t = \frac{\eta_n}{(1-\eta_n)\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]} \mathbf{J}_t.$$

To find an explicit Nash wage expression, first replace $\mathbf{M}_t$ and $\mathbf{J}_t$ into the surplus sharing rule to obtain

$$\frac{h'(lfp_t) - u'(c_t)\chi}{u'(c_t)f(\theta_t)} = \frac{\eta_n}{(1-\eta_n)\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]} \left[\frac{\gamma\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]}{q(\theta_t)}\right].$$

Then, use the job creation condition on the right-hand-side:

$$\begin{aligned}
\frac{h'(lfp_t) - u'(c_t)\chi}{u'(c_t)f(\theta_t)} \quad = \quad & \left(\frac{\eta_n}{(1-\eta_n)\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]}\right) \\
& \cdot \left[\begin{array}{l} A_t f_n(n_t, k_t) - w_t \left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_{l,t}\right] \\ +(1-\rho^n) E_t \Xi_{t+1|t} \left[\frac{\gamma\left[(1-\phi) + \phi \Xi_{t+2|t+1} R_{l,t+1}\right]}{q(\theta_{t+1})}\right] \end{array}\right].
\end{aligned}$$

Use the household's participation condition on the left-hand-side:

$$\begin{aligned}
& \left[w_t - \chi + (1-\rho^n) E_t \Xi_{t+1|t} \left(\frac{1 - f(\theta_{t+1})}{f(\theta_{t+1})}\right) \left(\frac{h'(lfp_{t+1})}{u'(c_{t+1})} - \chi\right)\right] \\
= \quad & \frac{\eta_n}{(1-\eta_n)\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]} \left[\begin{array}{l} A_t f_n(n_t, k_t) - w_t \left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_{l,t}\right] \\ +(1-\rho^n) E_t \Xi_{t+1|t} \left[\frac{\gamma\left[(1-\phi) + \phi \Xi_{t+2|t+1} R_{l,t+1}\right]}{q(\theta_{t+1})}\right] \end{array}\right].
\end{aligned}$$

Multiply both sides by $(1-\eta_n)\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]$ to get

$$\begin{aligned}
&(1-\eta_n)\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]\left[\begin{array}{c} w_t-\chi \\ +(1-\rho^n)E_t\Xi_{t+1|t}\left(\frac{1-f(\theta_{t+1})}{f(\theta_{t+1})}\right)\left(\frac{h'(lfp_{t+1})}{u'(c_{t+1})}-\chi\right)\end{array}\right] \\
= \;& \eta_n\left[\begin{array}{c} A_tf_n(n_t,k_t)-w_t\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_{l,t}\right] \\ +(1-\rho^n)E_t\Xi_{t+1|t}\left[\frac{\gamma\left[(1-\phi)+\phi\Xi_{t+2|t+1}R_{l,t+1}\right]}{q(\theta_{t+1})}\right]\end{array}\right].
\end{aligned}$$

Using the surplus sharing rules in $t+1$, we can write this as

$$\begin{aligned}
&(1-\eta_n)\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]\left[\begin{array}{c} w_t-\chi \\ +(1-\rho^n)E_t\Xi_{t+1|t}\left(1-f(\theta_{t+1})\right) \\ \cdot\left(\frac{\eta_n}{(1-\eta_n)\left[(1-\phi)+\phi\Xi_{t+2|t+1}R_{t+1}^l\right]}\mathbf{J}_{t+1}\right)\end{array}\right] \\
= \;& \eta_n\left[\begin{array}{c} A_tf_n(n_t,k_t)-w_t\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_{l,t}\right] \\ +(1-\rho^n)E_t\Xi_{t+1|t}\mathbf{J}_{t+1}\end{array}\right].
\end{aligned}$$

Now solve for w_t :

$$\begin{aligned}
w_t \;=\;& \frac{\eta_nA_tf_n(n_t,k_t)}{\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]}+\frac{\eta_n(1-\rho^n)}{\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]}E_t\Xi_{t+1|t}\mathbf{J}_{t+1} \\
&+(1-\eta_n)\chi-(1-\rho^n)E_t\Xi_{t+1|t}\left(1-f(\theta_{t+1})\right)\left(\frac{\eta_n}{\left[(1-\phi)+\phi\Xi_{t+2|t+1}R_{t+1}^l\right]}\mathbf{J}_{t+1}\right).
\end{aligned}$$

Using $\mathbf{J}_{t+1}\equiv\frac{\gamma\left[(1-\phi)+\phi E_{t+1}\Xi_{t+2|t+1}R_{t+1}^l\right]}{q(\theta_{t+1})}$, we have

$$\begin{aligned}
w_t \;=\;& \frac{\eta_nA_tf_n(n_t,k_t)}{\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]}+\eta_n(1-\rho^n)E_t\Xi_{t+1|t}\left(\frac{\gamma}{q(\theta_{t+1})}\frac{\left[(1-\phi)+\phi E_{t+1}\Xi_{t+2|t+1}R_{t+1}^l\right]}{\left[(1-\phi)+\phi E_t\Xi_{t+1|t}R_t^l\right]}\right) \\
&+(1-\eta_n)\chi-\eta_n(1-\rho^n)E_t\Xi_{t+1|t}\left(1-f(\theta_{t+1})\right)\left(\frac{\gamma}{q(\theta_{t+1})}\right).
\end{aligned}$$

Finally, combining terms, we can rewrite this as

$$\begin{aligned} w_t &= \frac{\eta_n A_t f_n(n_t, k_t)}{\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]} + (1-\eta_n)\chi \\ &+\eta_n (1-\rho^n) E_t \Xi_{t+1|t} \left[\frac{\gamma}{q(\theta_{t+1})} \left(\frac{\left[(1-\phi) + \phi E_{t+1} \Xi_{t+2|t+1} R_{t+1}^l\right]}{\left[(1-\phi) + \phi E_t \Xi_{t+1|t} R_t^l\right]} - [1 - f(\theta_{t+1})]\right)\right]. \end{aligned} \tag{24}$$

Note that absent any working capital constraints (i.e., $\phi = 0$), the above expression collapses to

$$w_t = \eta_n A_t f_n(n_t, k_t) + (1-\eta_n)\chi + \eta_n (1-\rho^n) E_t \Xi_{t+1|t} \theta_{t+1} \gamma,$$

which is the exact expression in Arseneau and Chugh (2012) absent distortionary taxes.

E Business Cycle Statistics: Additional Results in Benchmark Model

Table A4 shows a version of Table 3 in the main text where we shut down each of the shocks or mechanisms in the benchmark model *without recalibrating any of the model variants.* The conclusions from Table 3 in the main text remain unchanged.

Table A5 compares the benchmark model under the baseline calibration to the same (recalibrated) model under alternative parameterizations. In particular, we consider the benchmark model with: lower deep habits in credit markets ($\omega = 0.5$ vs. the baseline $\omega = 0.72$); higher and lower values for the length of lending relationships ($\rho_s = 0.90$ and $\rho_s = 0.30$ vs. the baseline $\rho_s = 0.50$); lower persistence of financial shocks ($\rho_\xi = 0.50$ and $\rho_\xi = 0$ vs. the baseline $\rho_\xi = 0.90$). Our main conclusions remain unchanged. Finally, we consider a version of the model where the wage bill is not part of the firms' working capital constraint. The table shows that the presence of the wage bill in the working capital constraint is critical for generating high volatility in vacancies and unemployment.

Table A6 compares the benchmark model with recalibrated versions of the same model with lower values for deep habits ω. In particular, we consider values for ω of 0.5, 0.3, and 0.1 (vs. 0.72 in the baseline calibration). *Conditional on matching the volatility of* *labor force participation (LFP) and spreads*, the value of ω itself has marginal effects on the benchmark's model ability to generate high volatility in unemployment and vacancies amid consistent macroeconomic dynamics.

Table A7 compares the benchmark model under the baseline calibration to: (1) a variant of the benchmark model where financial shocks enter via stochastic fluctuations in the degree of deep habits ω; (2) a variant of the benchmark model where financial shocks enter via stochastic fluctuations in the household's subjective discount factor β; (3) a variant of the benchmark model with exogenous countercyclical spreads; (4) a version of the benchmark model without aggregate productivity shocks; and (5) a version of the benchmark model without financial shocks and without deep habits (i.e., $\omega = 0$). First, introducing financial shocks via stochastic movements in ω generates virtually identical cyclical dynamics compared to the benchmark model. Second, while shocks to β that match the volatility of spreads generate high volatility in vacancies and unemployment, these dynamics come at a cost of producing highly volatile and countercyclical consumption.[20] Third, assuming exogenous countercyclical spreads instead of endogenous countercyclical spreads still generates high unemployment volatility, but reduces the volatility of vacancies, implying that the benchmark model offers a better overall fit with the data. Fourth, abstracting from aggregate productivity shocks implies that the volatility of spreads is much higher than in the data, which translates into highly volatile vacancies and unemployment and a fall in the procyclicality of consumption and investment compared to the benchmark model. Finally, abstracting from both financial shocks and deep habits implies that the benchmark model produces only 20 percent of the volatility of unemployment and vacancies in the data.

As discussed in the main text, Table A8 shows that our main findings remain unchanged if we set the matching elasticity μ equal to the workers' bargaining power η_n in a recalibrated version of the benchmark model (given our baseline calibration we consider two cases, $\mu = \eta_n = 0.5$ and $\mu = \eta_n = 0.4$). As also noted in the main text, a version of the benchmark model that adopts a calibration in the spirit of Hagedorn-Manovskii (HM) does generate even

[20]This result traces back to the magnitude of β shocks needed to match the volatility of spreads: β shocks need to be very large to match this second moment. Reducing the magnitude of these shocks reduces the volatility of spreads in the model relative to the data, and for small-enough shocks, we recover the procyclicality and low volatility (relative to output) of consumption.

greater labor market volatility, but produces countercyclical consumption and investment (see the main text for a brief explanation of this outcome). Table A9 presents more details behind the impact of alternative values for the bargaining power of workers by comparing the benchmark model to the same model under two different values for the bargaining power, $\eta_n = 0.3$ and $\eta_n = 0.2$ (in this case, we assume a replacement rate of 50 percent of steady-state wages, as in the benchmark model). For completeness, we show results when we recalibrate the model to match the same second moments as the benchmark model, and versions where we simply lower η_n without matching the volatility of LFP and spreads. The model still generates high volatility in vacancies and unemployment, though a lower bargaining power lowers the procyclicality of consumption and investment relative to both the data and the benchmark model.

Table A10 compares the benchmark model to a version of the same model with countercyclical movements in job separation probabilities that are driven by movements in (1) credit spreads or (2) aggregate productivity. In particular, we assume that job separation probabilities increase with an increase in spreads and with a decrease in aggregate productivity so as to match the volatility of job separation rates in the data in addition to our two other targets (i.e., the volatilities of spreads and LFP). These benchmark-model variants continue to produce factual macroeconomic dynamics amid highly volatile vacancies and unemployment. In fact, the volatility of unemployment is higher in these model variants than in the data.

Tables A11 and A12 compare the leads and lags of select variables with output in the data to those generated by the benchmark model and a version of the benchmark model with constant LFP, and shows that the benchmark model does well in capturing these moments.

Finally, Table A13 shows a version of Table 3 where we shut down aggregate productivity shocks so that only financial shocks drive business cycles. The table compares the benchmark model to a version with constant and exogenous LFP. To do so, we simply shut down aggregate productivity shocks while keeping the same parameters for the financial-shock process. The reason for this choice is as follows: without aggregate productivity shocks, the ratio of the volatility of spreads to the volatility of output is independent of the standard deviation of financial shocks. However, the *absolute* volatility of spreads *is* dependent on the size of financial shocks. Since we are focusing on relative volatilities, changing the volatility of financial shocks will not affect any of the second moments we are interested in. As such, we simply use the volatility of financial shocks from the baseline calibration. Hence the fact that in Table A13 the relative volatility of spreads is no longer a targeted second moment. While the model generates *qualitatively*-factual business cycles that are similar to those in the model with both aggregate productivity and financial shocks, abstracting from aggregate productivity shocks implies, from a *quantitative* standpoint and relative to the business cycle dynamics generated by our baseline calibration: a much stronger countercyclicality in spreads and unemployment; much more volatile spreads, which bolsters the volatility of vacancies and unemployment; and a lower procyclicality of consumption. This holds in both the benchmark model and in the model with constant and constatnt participation. In particular, note that vacancies and unemployment are highly volatile, which traces back to the much higher volatility and countercyclicality of spreads relative to the data. Of course, this experiment is only meant to illustrate the role of financial shocks *alone* in generating factual business cycle dynamics and not meant to suggest that business cycles are better explained by financial shocks only. This experiment also suggests that from a quantitative standpoint, a model with both aggregate productivity and financial shocks, and not just one set of shocks, provides a better overall quantitative fit with the data, not only with respect to the labor market, but also with respect to other macroeconomic variables. More broadly, the results in Table A13 are consistent with the findings in Jermann and Quadrini (2012), Epstein et al. (2017), and others who have highlighted the relevance financial shocks *alongside* aggregate productivity shocks for quantitatively capturing (labor market) and macroeconomic dynamics.

Targeted Moments	Data	Benchmark Model	Benchmark, No Fin. Shocks	Benchmark, $\omega = 0$	Constant LFP	Constant LFP, No Fin. Shocks	Constant LFP, $\omega = 0$
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.044	0.146	-	-	-
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	4.093*	25.15*	28.170	4.133*	24.53*
Non-Targeted Moments							
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.342	0.332	0.333	0.348	0.346
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	2.927	2.882	2.871	2.932	2.899
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	3.085	9.718	3.742	1.068	3.374
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	2.903	7.113	4.120	1.267	3.510
$corr(c_t, y_t)$	0.898	0.806	0.911	0.845	0.844	0.918	0.869
$corr(inv_t, y_t)$	0.899	0.922	0.990	0.950	0.947	0.992	0.962
$corr(ur_t, y_t)$	-0.856	-0.716	-0.986	-0.640	-0.482	-0.715	-0.449
$corr(v_t, y_t)$	0.881	0.504	0.637	0.473	0.603	0.908	0.551
$corr(lfp_t, y_t)$	0.332	0.636	0.801	0.561	-	-	-
$corr(spread_t, y_t)$	-0.664	-0.563	-0.556	-0.460	-0.452	-0.545	-0.356

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4. * denotes a non-targeted moment.

Table A4: Business Cycle Statistics - Data vs. Benchmark Model and Model Variants (No Recalibration)

Targeted Moments	Data	Benchmark Model	Benchmark, $\omega = 0.5$	Benchmark, Higher $\rho^s = 0.90$	Benchmark, Lower $\rho^s = 0.30$	Benchmark, Lower $\rho_\xi = 0.50$	Benchmark, Lower $\rho_\xi = 0$	Benchmark, No Wage Bill in WK Constraint
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.171	0.171	0.171	0.171	0.171
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	28.17	28.17	28.17	28.17	28.17
Non-Targeted Moments								
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.319	0.310	0.308	0.303	0.305	0.340
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	2.861	2.838	2.843	2.870	2.856	2.921
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	10.798	10.968	10.359	10.543	9.819	6.391
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	8.239	8.173	10.791	11.751	14.281	4.347
$corr(c_t, y_t)$	0.898	0.806	0.818	0.808	0.799	0.761	0.769	0.880
$corr(inv_t, y_t)$	0.899	0.922	0.935	0.938	0.882	0.864	0.786	0.980
$corr(ur_t, y_t)$	-0.856	-0.716	-0.689	-0.731	-0.734	-0.718	-0.717	-0.587
$corr(v_t, y_t)$	0.881	0.504	0.498	0.532	0.496	0.494	0.500	0.528
$corr(lfp_t, y_t)$	0.332	0.636	0.615	0.662	0.632	0.618	0.594	0.911
$corr(spread_t, y_t)$	-0.664	-0.563	-0.536	-0.593	-0.568	-0.555	-0.537	-0.317

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4. * denotes a non-targeted moment.

Table A5: Business Cycle Statistics - Data vs. Benchmark Model and Model with Lower Deep Habits, Long-Lasting Lending Relationships, Lower Persistence of Financial Shocks, and no Wage-Bill Frictions

Targeted Moments	Data	Benchmark Model	Benchmark, $\omega = 0.5$	Benchmark, $\omega = 0.3$	Benchmark, $\omega = 0.1$
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.171	0.171
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	28.17	28.17
Non-Targeted Moments					
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.319	0.321	0.321
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	2.861	2.863	2.865
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	10.798	10.811	10.816
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	8.239	8.069	7.992
$corr(c_t, y_t)$	0.898	0.806	0.818	0.821	0.822
$corr(inv_t, y_t)$	0.899	0.922	0.935	0.937	0.938
$corr(ur_t, y_t)$	-0.856	-0.716	-0.689	-0.681	-0.677
$corr(v_t, y_t)$	0.881	0.504	0.498	0.495	0.494
$corr(lfp_t, y_t)$	0.332	0.636	0.615	0.608	0.604
$corr(spread_t, y_t)$	-0.664	-0.563	-0.536	-0.527	-0.523

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4. * denotes a non-targeted moment.

Table A6: Business Cycle Statistics - Data vs. Benchmark Model under Baseline Calibration and (Recalibrated) Benchmark Model with Lower Deep-Habits Parameter (ω) Values

Targeted Moments	Data	Benchmark Model	Benchmark, Shocks to ω	Benchmark, Shocks to β	Benchmark, Exog. Countercyclical Spreads	Benchmark, No TFP Shocks	Benchmark, No Fin. Shocks and $\omega = 0$
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.171	0.17	0.171	0.171
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	28.17	27.47	54.62*	0.032*
Non-Targeted Moments							
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.304	2.011	0.356	0.156	0.346
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	2.863	5.128	2.189	2.663	2.951
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	10.796	16.353	11.482	20.717	1.971
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	9.009	21.608	6.921	16.195	2.019
$corr(c_t, y_t)$	0.898	0.806	0.799	-0.387	0.960	0.489	0.922
$corr(inv_t, y_t)$	0.899	0.922	0.925	0.816	0.956	0.750	0.993
$corr(ur_t, y_t)$	-0.856	-0.716	-0.743	-0.843	-0.962	-0.997	-0.813
$corr(v_t, y_t)$	0.881	0.504	0.508	0.625	0.888	0.706	0.760
$corr(lfp_t, y_t)$	0.332	0.636	0.656	0.538	1.000	0.940	0.959
$corr(spread_t, y_t)$	-0.664	-0.563	-0.589	-0.715	-1.000	-0.954	0.961

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4. The benchmark-model variants with an exogenous spread rule have neither deep habits nor financial shocks since the lending rate is simply given by $R^l_t = R_{d,t}(1 + spread_t)$, where $spread_t$ responds to output deviations from trend: $spread_t = \alpha_l(y_{ss} - y_t)$ where α_l is calibrated to match the relative volatility of lending spreads in the data. Of note, absent deep habits and given the spread specification we adopt, the cyclical correlation of the lending spread is -1. * denotes a non-targeted moment.

Table A7: Business Cycle Statistics - Data vs. Benchmark Model and (Recalibrated) Model Variants with Alternative Shock Specifications

Targeted Moments	Data	Benchmark Model	Benchmark, $\eta_n = 0.20$	Benchmark, $\eta_n = \mu = 0.4$	Benchmark, $\eta_n = \mu = 0.5$	Benchmark HM (2008) Calibration
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.171	0.171	0.171
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	28.17	28.17	28.17
Non-Targeted Moments						
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.313	0.304	0.320	0.280
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	4.485	2.873	2.852	5.578
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	10.291	10.689	8.429	18.577
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	10.156	9.171	8.372	15.273
$corr(c_t, y_t)$	0.898	0.806	0.482	0.756	0.818	-0.581
$corr(inv_t, y_t)$	0.899	0.922	0.222	0.820	0.935	-0.161
$corr(ur_t, y_t)$	-0.856	-0.716	-0.695	-0.712	-0.644	-0.919
$corr(v_t, y_t)$	0.881	0.504	0.500	0.504	0.492	0.687
$corr(lfp_t, y_t)$	0.332	0.636	0.616	0.633	0.563	0.859
$corr(spread_t, y_t)$	-0.664	-0.563	-0.546	-0.560	-0.470	-0.829

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4.

Table A8: Business Cycle Statistics - Data vs. Benchmark Model and Model with Alternative Worker Bargaining Power Values, Hosios, and Hagedorn and Manovskii (2008) Calibration

Targeted Moments	Data	Benchmark Model	Benchmark, $\eta_n = 0.30$ Recalibrated	Benchmark, $\eta_n = 0.30$ No Recab.	Benchmark, $\eta_n = 0.20$ Recalibrated	Benchmark, $\eta_n = 0.20$ No Recab.
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.183*	0.171	0.199*
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	29.22*	28.17	30.87*
Non-Targeted Moments						
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.299	0.295	0.313	0.308
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	3.191	3.226	4.485	4.807
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	10.590	10.949	10.291	11.179
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	9.479	9.846	10.156	11.171
$corr(c_t, y_t)$	0.898	0.806	0.661	0.639	0.482	0.388
$corr(inv_t, y_t)$	0.899	0.922	0.596	0.569	0.222	0.139
$corr(ur_t, y_t)$	-0.856	-0.716	-0.706	-0.716	-0.695	-0.719
$corr(v_t, y_t)$	0.881	0.504	0.502	0.510	0.500	0.522
$corr(lfp_t, y_t)$	0.332	0.636	0.627	0.640	0.616	0.649
$corr(spread_t, y_t)$	-0.664	-0.563	-0.556	-0.575	-0.546	-0.593

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4.

Table A9: Business Cycle Statistics - Data vs. Benchmark Model and Model with Alternative Worker Bargaining Power Values

Targeted Moments	Data	Benchmark Model	Benchmark, Countercycl. Sep. with Spreads	Benchmark, Countercycl. Sep. with TFP	Benchmark, Countercycl. Sep. with TFP No Fin. Shocks
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	0.171	0.171
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	28.17	4.514*
$\sigma_{rho_t^n}/\sigma_{y_t}$	6.034	-	6.03	6.032	6.033
Non-Targeted Moments					
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.312	0.319	0.453	0.480
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.851	3.213	3.164	3.294
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.732	16.179	13.060	8.313
$\sigma_{v_t}/\sigma_{y_t}$	9.383	8.983	7.226	9.771	5.214
$corr(c_t, y_t)$	0.898	0.806	0.843	0.844	0.952
$corr(inv_t, y_t)$	0.899	0.922	0.937	0.918	0.975
$corr(ur_t, y_t)$	-0.856	-0.716	-0.857	-0.938	-0.981
$corr(v_t, y_t)$	0.881	0.504	0.266	0.057	-0.501
$corr(lfp_t, y_t)$	0.332	0.636	0.795	0.638	0.740
$corr(spread_t, y_t)$	-0.664	-0.563	-0.772	-0.559	-0.499
$corr(rho_t^n, y_t)$	-0.535	-	-0.772	-0.817	-0.995

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4.

Table A10: Business Cycle Statistics - Data vs. Benchmark Model and (Recalibrated) Benchmark Model with Time-Varying Job Separations

$j =$	-4	-3	-2	-1	0	1	2	3	4
					$Corr(GDP_t, x_{t+j})$				
Data									
Consump.	0.253	0.461	0.658	0.822	0.898	0.833	0.706	0.546	0.359
Invest.	0.410	0.547	0.704	0.824	0.899	0.786	0.590	0.341	0.132
Un. Rate	-0.202	-0.371	-0.555	-0.723	-0.856	-0.885	-0.828	-0.701	-0.541
LFP	-0.212	-0.107	0.056	0.215	0.332	0.431	0.483	0.515	0.488
Vacancies	0.382	0.558	0.719	0.831	0.882	0.816	0.683	0.512	0.315
Spread	-0.509	-0.632	-0.702	-0.710	-0.664	-0.566	-0.452	-0.325	-0.197
Model									
Consump.	-0.077	0.070	0.259	0.511	0.806	0.730	0.641	0.553	0.456
Invest.	0.168	0.299	0.465	0.677	0.922	0.821	0.551	0.311	0.120
Un. Rate	-0.094	-0.206	-0.351	-0.535	-0.716	-0.558	-0.342	-0.171	-0.047
LFP	0.128	0.230	0.354	0.511	0.636	0.300	0.118	0.012	-0.059
Vacancies	0.128	0.215	0.312	0.435	0.504	0.023	-0.089	-0.106	-0.109
Spread	-0.099	-0.192	-0.305	-0.449	-0.563	-0.276	-0.115	-0.018	0.044

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4.
Un. Rate denotes the unemployment rate.

Table A11: Business Cycle Statistics - Lags and Leads, Data vs. Benchmark Model

$j =$	-4	-3	-2	-1	0	1	2	3	4
					$Corr(GDP_t, x_{t+j})$				
Data									
Consump.	0.253	0.461	0.658	0.822	0.898	0.833	0.706	0.546	0.359
Invest.	0.410	0.547	0.704	0.824	0.899	0.786	0.590	0.341	0.132
Un. Rate	-0.202	-0.371	-0.555	-0.723	-0.856	-0.885	-0.828	-0.701	-0.541
Vacancies	0.382	0.558	0.719	0.831	0.882	0.816	0.683	0.512	0.315
Spread	-0.509	-0.632	-0.702	-0.710	-0.664	-0.566	-0.452	-0.325	-0.197
Model									
Consumption	-0.049	0.105	0.298	0.551	0.844	0.751	0.648	0.550	0.447
Investment	0.199	0.335	0.501	0.711	0.947	0.787	0.528	0.304	0.120
Un. Rate	-0.029	-0.100	-0.201	-0.327	-0.482	-0.631	-0.474	-0.294	-0.152
Vacancies	0.121	0.220	0.338	0.481	0.603	0.314	0.150	0.050	-0.018
Spread	-0.094	-0.170	-0.261	-0.370	-0.452	-0.210	-0.080	-0.003	0.045

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4.
Un. Rate denotes the unemployment rate.

Table A12: Business Cycle Statistics - Lags and Leads, Data vs. Benchmark Model with Constant Labor Force Participation

Targeted Moments	Data	Benchmark Model, No TFP Shocks	Benchmark, $\omega = 0$, No TFP Shocks	Constant LFP No TFP Shocks	Constant LFP, $\omega = 0$, No TFP Shocks
$\sigma_{lfp_t}/\sigma_{y_t}$	0.171	0.171	0.171	-	-
Non-Targeted Moments					
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	53.620	53.900	64.350	62.103
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.156	0.164	0.151	0.156
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.663	2.655	2.622	2.608
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	20.717	20.697	8.328	8.329
$\sigma_{v_t}/\sigma_{y_t}$	9.383	16.195	14.518	9.168	8.714
$corr(c_t, y_t)$	0.898	0.489	0.527	0.444	0.470
$corr(inv_t, y_t)$	0.899	0.750	0.810	0.743	0.795
$corr(ur_t, y_t)$	-0.856	-0.997	-0.997	-0.782	-0.832
$corr(v_t, y_t)$	0.881	0.706	0.712	0.939	0.950
$corr(lfp_t, y_t)$	0.332	0.940	0.946	-	-
$corr(spread_t, y_t)$	-0.664	-0.954	-0.953	-0.946	-0.952

Notes: Empirical moments based on HP-filtered data with smoothing parameter 1600 from 1987Q1-2017Q4.

Table A13: Business Cycle Statistics - Data vs. Benchmark Model without TFP Shocks and Benchmark Model with Constant Participation and without TFP Shocks

VAR Equation	**Excluded Variable**	χ^2	DF	Prob. $> \chi^2$
Unemployment Rate	Spread	4.2993	1	0.038
Vacancies	Spread	4.4079	1	0.036
Participation Rate	Spread	4.8421	1	0.028

Table A14: Granger Causality Tests with Simulated Data from Benchmark Model

F Impulse Response Functions: Additional Results

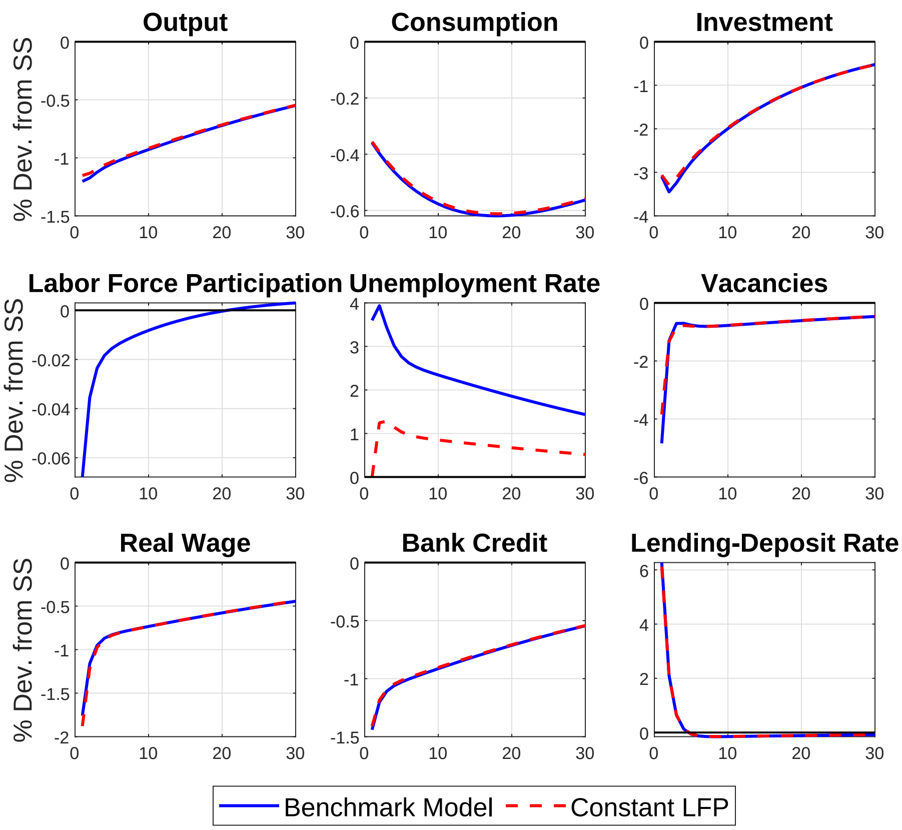

Figure A2: Response to a One-Standard-Deviation Reduction in Aggregate Productivity (Quarters after Shock)-Benchmark Model vs. Model with Constant Participation (Normalized Impulse Response Functions)

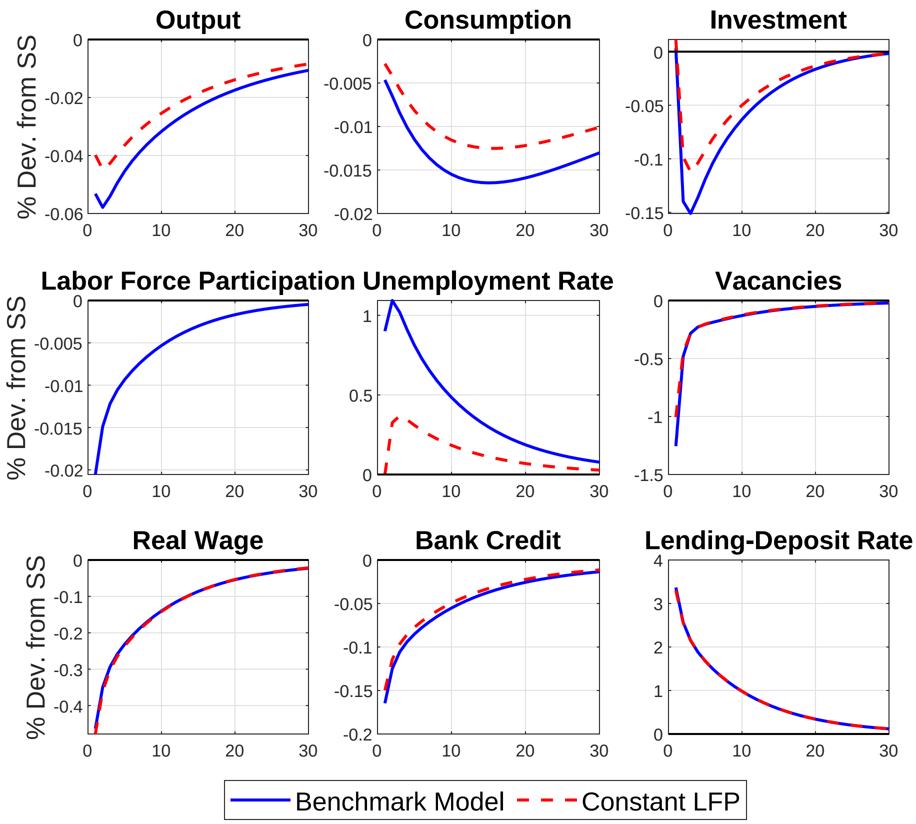

Figure A3: Response to a One-Standard-Deviation Adverse Financial Shock via Shock to ω (Quarters after Shock)-Benchmark Model vs. Model with Constant Participation (Normalized Impulse Response Functions)