ONLINE APPENDIX: Lending Relationships and Labor Market Dynamics

Alan Finkelstein Shapiro* María Pía Olivero†

May 12, 2020

*Department of Economics, Tufts University. E-mail: Alan.Finkelstein_Shapiro@tufts.edu.

†School of Economics, Drexel University and Department of Economics, Swarthmore College. Email: maria.olivero@drexel.edu.

A Data Details

Section 2 uses data for the period 1987Q1-2017Q4 to establish stylized facts linking credit spreads, 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 10-Year U.S. Treasury Yield, 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 Data			
Credit Spread	0.5519*	-0.2668*	-0.5569*
	(0.0000)	(0.0000)	(0.0000)
CF-Filtered Data			
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, Labor Force 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 credit spreads) 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 Tests: 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 credit 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:

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

where X_t is a vector of endogenous variables that includes real GDP growth, the credit spread, and 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 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 $Var(\epsilon)$. 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

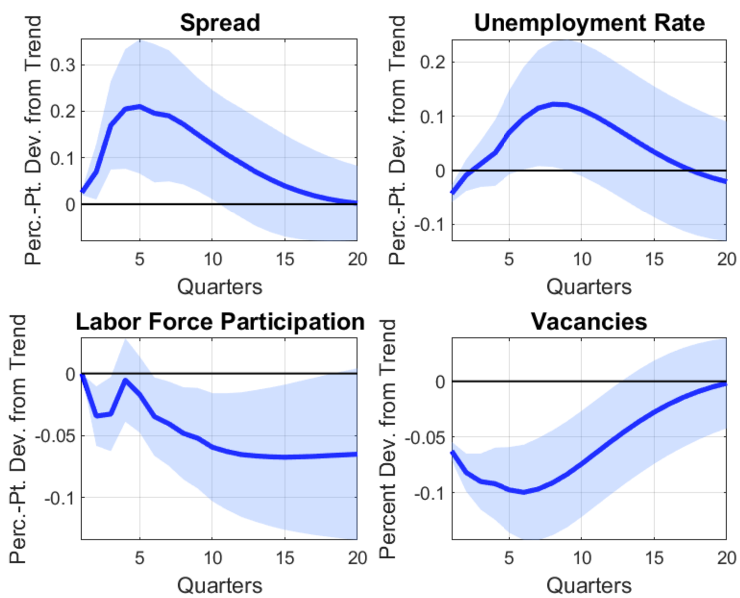

Figure A1: Response of Unemployment Rate, Labor Force Participation Rate, and Vacancies to a One-Percentage-Point Increase in Credit Spreads, Alternative Identification Restrictions

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:

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

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

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

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

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

Now solve for w_t :

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

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

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

Finally, combining terms, we can rewrite this as

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

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) in the absence of distortionary taxation.

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 $\rho_s = 0.66$ vs. the baseline $\rho_s = 0.85$); 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.[1] 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

[1] 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 of consumption (relative to output).

model that adopts a calibration in the spirit of Hagedorn-Manovskii (HM) does generate even 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 results where we simply lower η_n without recalibrating the model to match 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 fall 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 empirical leads and lags of select variables with real GDP to those generated by the benchmark model and a version of the benchmark model with constant LFP. The tables confirm 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 of the model with both aggregate productivity and financial shocks, abstracting from aggregate productivity shocks implies the following differences 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 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	5.491*	17.38*	28.170	4.133*	16.36*
Non-Targeted Moments							
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.301	0.333	0.351	0.331	0.348	0.358
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	2.904	2.917	2.856	2.932	2.927
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	3.774	6.905	2.932	1.068	2.328
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	3.128	5.003	4.106	1.267	2.416
$corr(c_t, y_t)$	0.898	0.774	0.903	0.886	0.847	0.918	0.899
$corr(inv_t, y_t)$	0.899	0.917	0.991	0.972	0.950	0.992	0.979
$corr(ur_t, y_t)$	-0.856	-0.747	-0.976	-0.587	-0.454	-0.715	-0.423
$corr(v_t, y_t)$	0.881	0.520	0.692	0.449	0.573	0.908	0.540
$corr(lfp_t, y_t)$	0.332	0.664	0.859	0.481	-	-	-
$corr(spread_t, y_t)$	-0.664	-0.602	-0.751	-0.308	-0.414	-0.545	-0.229

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 $\rho_s = 0.66$	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	0.301	0.316	0.300	0.305	0.295	0.298	0.325
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	2.861	2.847	2.864	2.860	2.843	2.882
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	10.864	11.021	8.188	10.718	9.987	7.544
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	8.306	8.934	17.296	11.881	14.264	7.717
$corr(c_t, y_t)$	0.898	0.774	0.808	0.775	0.779	0.746	0.759	0.839
$corr(inv_t, y_t)$	0.899	0.917	0.935	0.928	0.675	0.862	0.788	0.942
$corr(ur_t, y_t)$	-0.856	-0.747	-0.698	-0.757	-0.791	-0.751	-0.751	-0.693
$corr(v_t, y_t)$	0.881	0.520	0.504	0.535	0.518	0.511	0.513	0.472
$corr(lfp_t, y_t)$	0.332	0.664	0.625	0.681	0.585	0.648	0.622	0.695
$corr(spread_t, y_t)$	-0.664	-0.602	-0.549	-0.620	-0.531	-0.596	-0.578	-0.477

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	0.301	0.316	0.319	0.321
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	2.861	2.863	2.865
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	10.864	10.835	10.822
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	8.306	8.094	7.998
$corr(c_t, y_t)$	0.898	0.774	0.808	0.817	0.821
$corr(inv_t, y_t)$	0.899	0.917	0.935	0.938	0.939
$corr(ur_t, y_t)$	-0.856	-0.747	-0.698	-0.685	-0.678
$corr(v_t, y_t)$	0.881	0.520	0.504	0.498	0.495
$corr(lfp_t, y_t)$	0.332	0.664	0.625	0.612	0.605
$corr(spread_t, y_t)$	-0.664	-0.602	-0.549	-0.533	-0.525

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	54.21*	0.032*
Non-Targeted Moments							
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.301	0.294	2.026	0.356	0.134	0.346
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	2.871	5.183	2.188	2.724	2.951
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	10.954	17.311	11.481	20.775	1.971
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	9.482	22.067	6.922	16.982	2.019
$corr(c_t, y_t)$	0.898	0.774	0.768	-0.427	0.960	0.338	0.922
$corr(inv_t, y_t)$	0.899	0.917	0.919	0.833	0.956	0.733	0.993
$corr(ur_t, y_t)$	-0.856	-0.747	-0.769	-0.876	-0.962	-0.998	-0.813
$corr(v_t, y_t)$	0.881	0.520	0.520	0.647	0.888	0.706	0.760
$corr(lfp_t, y_t)$	0.332	0.664	0.678	0.570	1.000	0.938	0.959
$corr(spread_t, y_t)$	-0.664	-0.602	-0.621	-0.766	-1.000	-0.948	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	Table A $\eta = 0.20$	Benchmark, $\eta = \mu = 0.4$	Benchmark, $\eta = \mu = 0.5$	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	0.301	0.285	0.294	0.313	0.207
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	4.716	2.869	2.837	5.681
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	10.392	10.853	8.385	16.730
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	10.814	9.732	8.750	15.017
$corr(c_t, y_t)$	0.898	0.774	0.574	0.739	0.806	-0.223
$corr(inv_t, y_t)$	0.899	0.917	0.142	0.796	0.930	-0.162
$corr(ur_t, y_t)$	-0.856	-0.747	-0.730	-0.744	-0.680	-0.892
$corr(v_t, y_t)$	0.881	0.520	0.520	0.520	0.509	0.662
$corr(lfp_t, y_t)$	0.332	0.664	0.648	0.662	0.595	0.812
$corr(spread_t, y_t)$	-0.664	-0.602	-0.588	-0.601	-0.511	-0.782

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	0.185*	0.171	0.202*
$\sigma_{spread_t}/\sigma_{y_t}$	28.17	28.17	28.17	29.54*	28.17	31.54*
Non-Targeted Moments						
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.301	0.299	0.281	0.285	0.274
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	3.191	3.299	4.716	5.165
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	10.590	11.208	10.392	11.500
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	9.479	10.597	10.814	12.127
$corr(c_t, y_t)$	0.898	0.774	0.661	0.653	0.574	0.481
$corr(inv_t, y_t)$	0.899	0.917	0.596	0.498	0.142	0.041
$corr(ur_t, y_t)$	-0.856	-0.747	-0.706	-0.750	-0.730	-0.754
$corr(v_t, y_t)$	0.881	0.520	0.502	0.530	0.520	0.546
$corr(lfp_t, y_t)$	0.332	0.664	0.627	0.672	0.648	0.683
$corr(spread_t, y_t)$	-0.664	-0.602	-0.556	-0.618	-0.588	-0.636

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

	$Corr(GDP_t, x_{t+j})$								
j =	-4	-3	-2	-1	0	1	2	3	4
Data									
Consumption	0.253	0.461	0.658	0.822	0.898	0.833	0.706	0.546	0.359
Investment	0.410	0.547	0.704	0.824	0.899	0.786	0.590	0.341	0.132
Unempl. 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									
Consumption	-0.098	0.046	0.237	0.487	0.774	0.710	0.631	0.548	0.454
Investment	0.132	0.266	0.441	0.665	0.917	0.835	0.562	0.303	0.096
Unempl. Rate	-0.039	-0.158	-0.325	-0.542	-0.747	-0.580	-0.330	-0.124	0.019
LFP	0.079	0.192	0.340	0.527	0.664	0.310	0.088	-0.043	-0.119
Vacancies	0.096	0.195	0.313	0.455	0.520	0.021	-0.130	-0.157	-0.151
Spread	-0.054	-0.158	-0.297	-0.473	-0.602	-0.282	-0.077	0.044	0.114

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

Targeted Moments	Data	Benchmark Model	Benchmark, Countercyclical Sep. with Spreads	Benchmark, Countercyclical Sep. with TFP	Benchmark, Countercyclical 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	5.794*
$\sigma_{rho_t^n}/\sigma_{y_t}$	6.034	-	6.035	6.032	6.033
Non-Targeted Moments					
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.301	0.280	0.443	0.470
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.854	3.341	3.172	3.287
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	10.893	16.053	13.465	8.991
$\sigma_{v_t}/\sigma_{y_t}$	9.383	9.496	7.600	10.098	4.908
$corr(c_t, y_t)$	0.898	0.774	0.751	0.820	0.946
$corr(inv_t, y_t)$	0.899	0.917	0.938	0.914	0.977
$corr(ur_t, y_t)$	-0.856	-0.747	-0.869	-0.947	-0.983
$corr(v_t, y_t)$	0.881	0.520	0.293	0.091	-0.487
$corr(lfp_t, y_t)$	0.332	0.664	0.802	0.666	0.808
$corr(spread_t, y_t)$	-0.664	-0.602	-0.781	-0.598	-0.700
$corr(rho_t^n, y_t)$	-0.535	-	-0.781	-0.820	-0.994

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

	$Corr(GDP_t, x_{t+j})$								
j =	-4	-3	-2	-1	0	1	2	3	4
Data									
Consumption	0.253	0.461	0.658	0.822	0.898	0.833	0.706	0.546	0.359
Investment	0.410	0.547	0.704	0.824	0.899	0.786	0.590	0.341	0.132
Unempl. 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	0.109	0.306	0.559	0.847	0.754	0.649	0.552	0.447
Investment	0.201	0.341	0.510	0.721	0.950	0.771	0.521	0.301	0.116
Unempl. Rate	-0.008	-0.070	-0.168	-0.295	-0.454	-0.609	-0.467	-0.279	-0.122
Vacancies	0.088	0.185	0.304	0.449	0.573	0.314	0.138	0.022	-0.051
Spread	-0.060	-0.132	-0.221	-0.329	-0.414	-0.195	-0.052	0.037	0.087

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					
$\sigma_{spread_t}/\sigma_{y_t}$	28.170	54.212	53.885	83.883	77.508
$\sigma_{c_t}/\sigma_{y_t}$	0.844	0.134	0.164	0.109	0.131
$\sigma_{inv_t}/\sigma_{y_t}$	5.184	2.724	2.655	2.492	2.402
$\sigma_{ur_t}/\sigma_{y_t}$	9.988	20.775	20.692	8.359	8.348
$\sigma_{v_t}/\sigma_{y_t}$	9.383	16.982	14.517	11.763	10.728
$corr(c_t, y_t)$	0.898	0.338	0.527	-0.042	0.006
$corr(inv_t, y_t)$	0.899	0.733	0.810	0.576	0.698
$corr(ur_t, y_t)$	-0.856	-0.998	-0.997	-0.753	-0.830
$corr(v_t, y_t)$	0.881	0.706	0.712	0.944	0.952
$corr(lfp_t, y_t)$	0.332	0.938	0.946	-	-
$corr(spread_t, y_t)$	-0.664	-0.948	-0.953	-0.947	-0.954

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

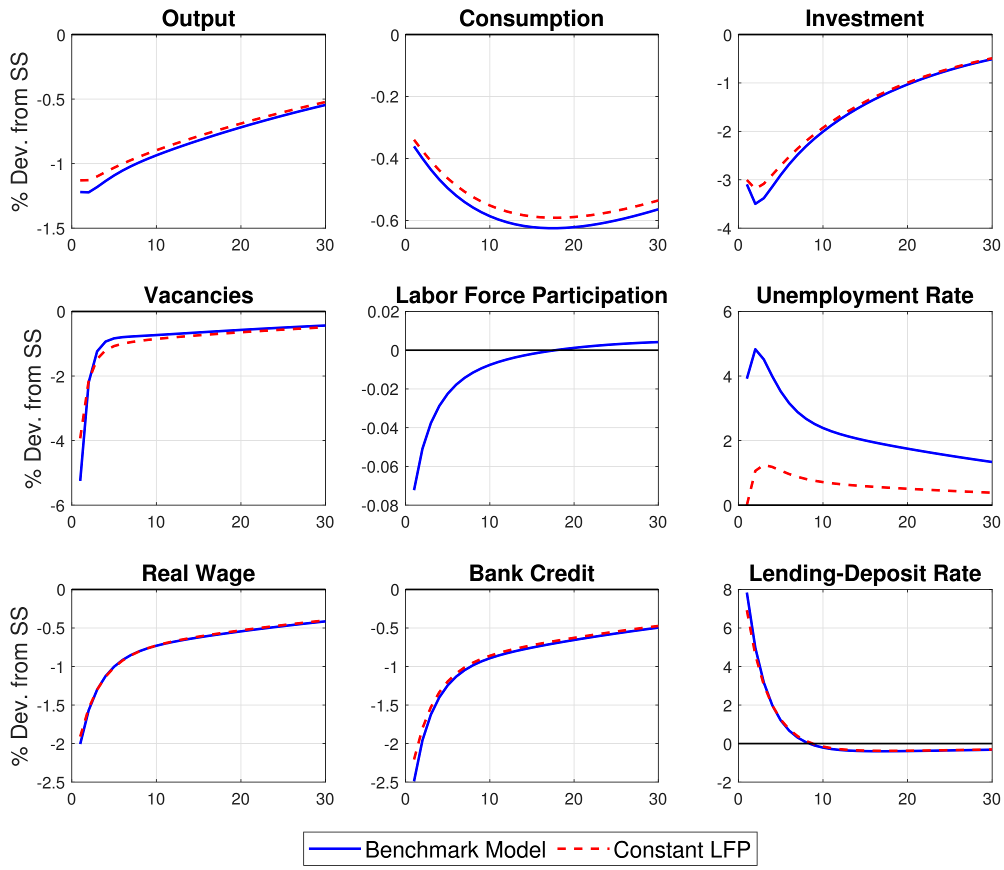

Figure A2: Response to a One-Standard-Deviation Reduction in Aggregate Productivity (Quarters after Shock)-Benchmark Model vs. Model with Constant Participation (Normalized Impulse Response Functions)

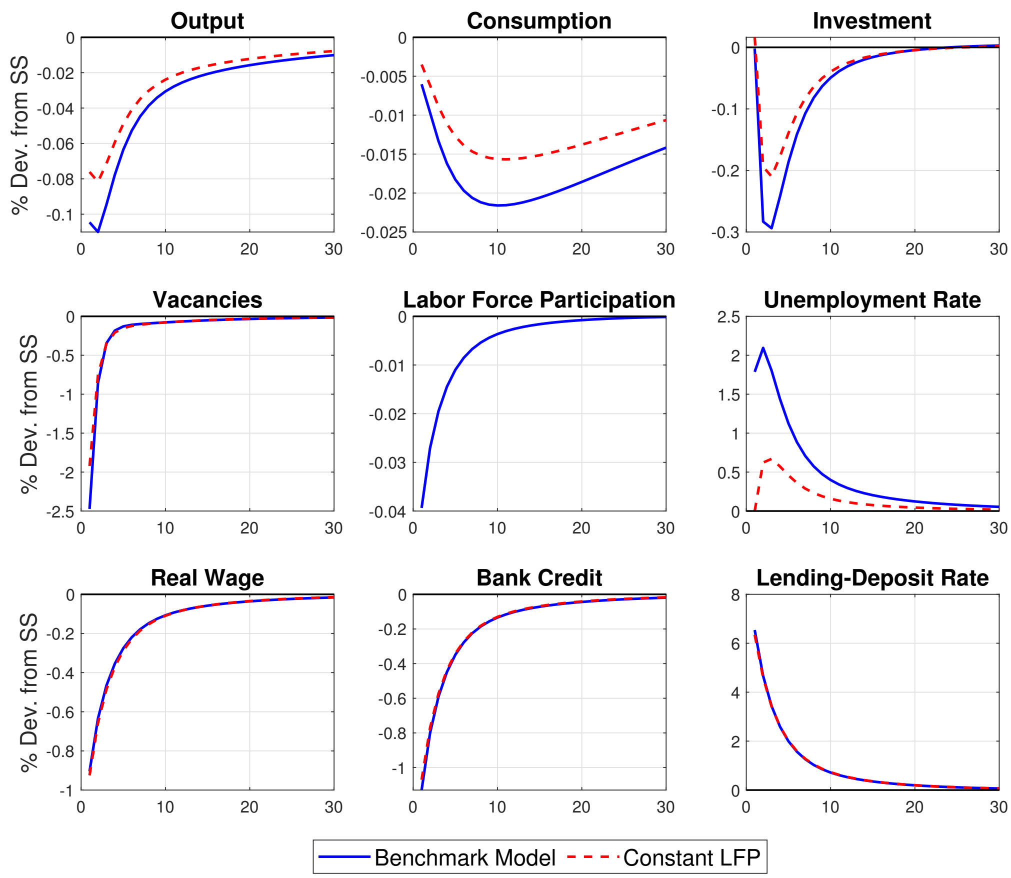

Figure A3: Response to a One-Standard-Deviation Adverse Financial Shock via Shock to ω (Quarters after Shock)-Benchmark Model vs. Model with Constant Participation (Normalized Impulse Response Functions)