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Macroeconomic Effects of Financial Shocks: Comment

By Johannes Pfeifer*

Urban Jermann and Vincenzo Quadrini (2012) argue that financial shocks are the most important factor driving U.S. business cycles. I show that the construction of their TFP measure suffers from data problems. A corrected TFP measure is able to account for most of the Great Recession. Their estimated DSGE model is also affected by several issues. In a properly reestimated model, marginal efficiency of investment shocks explain most of output volatility, while the contribution of financial shocks is 6.5 percent as opposed to the 46 percent originally reported. Still, financial shocks contribute 2-3 percentage points to the observed GDP drop during the Great Recession.

JEL: E23, E32, E44, G01, G32

Keywords: Financial Frictions, Pecking Order, Marginal Efficiency of Investment

Jermann and Quadrini (2012) (JQ) develop a DSGE model incorporating the pecking order theory of debt and equity financing to explore how the dynamics of real and financial variables are affected by financial shocks. They do so using two distinct approaches: their first approach uses a parsimonious model to construct a series of financial shocks and feeds these shocks together with standard Solow residual-based TFP shocks back into the model. They find that the Great Recession was strongly influenced by financial shocks. Their second approach estimates a medium-scale DSGE model using Bayesian full information techniques. They find that financial shocks account for almost half of the volatility of output growth since the beginning of the Great Moderation period.

I show that both approaches suffer from methodological issues. In their first approach, the constructed TFP measure combines GDP of the total economy with inputs pertaining to the private business sector only. In addition, JQ make a timing error by using the end of period

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rather than the beginning of period capital stock as an input, which is inconsistent with their model. Correcting these two issues leads to a more volatile TFP series. Recalibrating the model to match the calibration targets, TFP innovations mostly account for the Great Recession and the contribution of financial innovations is considerably muted.

JQ's second approach is affected by issues in three equilibrium conditions, in mode finding, and in convergence of the Metropolis-Hastings algorithm. When I fix these issues and reestimate the model, the posterior estimates are more consistent with the previous literature. In agreement with Alejandro Justiniano, Giorgio E. Primiceri and Andrea Tambalotti (2011), marginal efficiency of investment (MEI) shocks are found to be the most important driver of business cycles. In contrast, the contribution of financial shocks to aggregate volatility becomes small. They account for 6.5 percent of output variance as opposed to the 46 percent reported in JQ.

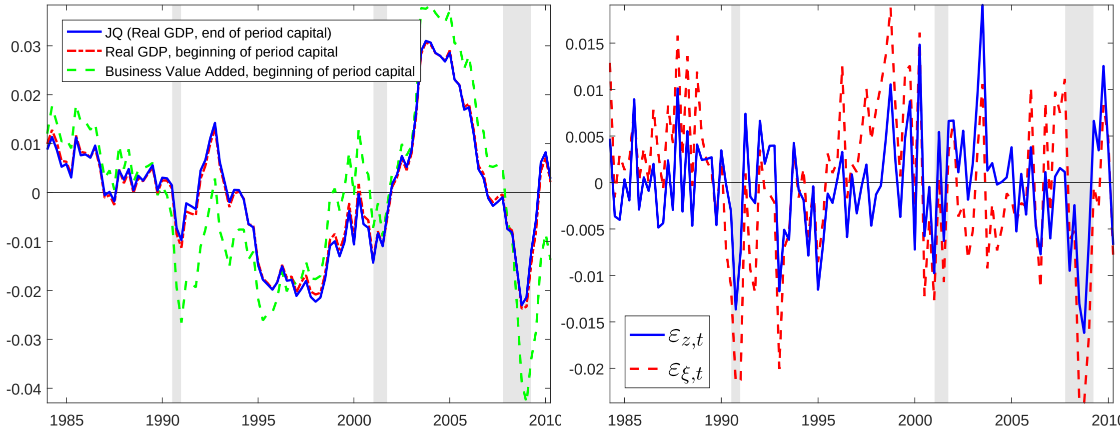
Thus, the empirical evidence from both approaches calls into question the importance of the particular type of microfounded financial shock proposed by JQ. Despite the small role of the JQ financial shocks for explaining aggregate volatility over the full sample, their role during the recent Great Recession episode is more pronounced, accounting for 2-3 percentage points of the 9 percentage point GDP drop.

The rest of the paper proceeds as follows. Section I considers the TFP shock construction in the parsimonious model. Section II reestimates the extended medium-scale DSGE model. Section III concludes.

I. Basic model

In their first approach, JQ use the equilibrium relationships of a parsimonious model to construct a series for financial conditions, $\hat{\xi}_t$. They then combine the series for financial conditions with a series for TFP constructed as the Solow residual, $\hat{z}_t$, and estimate the bivariate VAR:

$$\begin{pmatrix} \hat{z}_{t+1} \\ \hat{\xi}_{t+1} \end{pmatrix} = \mathbf{A} \begin{pmatrix} \hat{z}_t \\ \hat{\xi}_t \end{pmatrix} + \begin{pmatrix} \varepsilon_{z,t+1} \\ \varepsilon_{\xi,t+1} \end{pmatrix}, \tag{1}$$



(a) TFP series (b) VAR Residuals

Figure 1. : Constructed TFP series and estimated VAR residuals

Note: Left panel: time series of TFP based on real GDP and end of period capital stock used in JQ (blue solid line), TFP based on real GDP and beginning of period capital stock (red dashed-dotted line), and of TFP based on business value added and beginning of period capital stock (green dashed line). Right panel: time series of the estimated TFP residual $\varepsilon_{z,t}$ (blue solid line) and of the financial residual $\varepsilon_{\xi,t}$ (red dashed line) from the VAR with Business Gross Value Added TFP (BGVA-TFP). Shaded areas denote NBER recessions.

where $\mathbf{A}$ is a two by two coefficient matrix. TFP residuals $\varepsilon_{z,t+1}$ and financial residuals $\varepsilon_{\xi,t+1}$ are assumed to be i.i.d. with standard deviations σ_z and σ_ξ.

JQ construct the TFP series $\hat{z}_t$ that they feed into their bivariate VAR as the Solow residual

$$\hat{z}_t = \hat{y}_t - \theta\hat{k}_t - (1-\theta)\hat{n}_t \,, \tag{2}$$

where θ is the capital share, k_t is the *beginning* of period capital stock used in production, and hats denote percentage deviations from the long-run trend. There are two issues in JQ's construction of TFP. First, JQ use time series comprising a different number of sectors on the right-hand side of equation (2). The capital stock k_t is constructed from data of the nonfinancial corporate business sector. Similarly, hours n_t relate to the private business sector and are proxied by "Aggregate Weekly Hours: Production and Nonsupervisory Employees: Total Private Industries". Yet to measure output y_t, JQ use "Real gross domestic product", i.e. the full economy. According to JQ's technical appendix, they originally intended to use "Gross value added: GDP: Business" as their output measure. This would have treated the construction of TFP symmetrically to the construction of financial conditions ξ_t, which relies on gross value added in the private business sector. Yet, in their replication codes JQ actually use "Real gross domestic product" of the whole economy.

Second, JQ use the *end* of period capital stock constructed from the flow of funds table instead of the *beginning* of period one. This implies that the investment produced within the current quarter is already used to produce the same investment and contrasts with JQ's model, which assumes one period time-to-build.[1]

The left panel of Figure 1 shows the three different TFP series. The Business Gross Value Added TFP (BGVA-TFP) series (green dashed line) displays considerably larger fluctuations than the TFP series constructed using GDP of the whole economy. In particular, during the Great Recession the drop in TFP is almost twice as big.

The right panel of Figure 1 displays the time series of the estimated residuals of the VAR in equation (1) when using the BGVA-TFP measure. When constructing TFP $\hat{z}_t$ and the financial conditions $\hat{\xi}_t$ using the same sectoral output concept, the estimated shocks show a correlation of $\rho = 0.7425$ (p-value=$1.2484e-19$). This correlation between shocks in the historical sample when using the BGVA-TFP requires the model to be recalibrated with a dividend adjustment cost parameter $\kappa = 0.08$ as opposed to $\kappa = 0.146$ in JQ to still match the calibration targets (see Appendix B for details).[2]

The top row of Figure 2 reports the counterfactual data series from the recalibrated model simulated with only the TFP equation residual. The counterfactuals for the financial variables are relegated to Appendix C. Compared to JQ (red dashed line), BGVA-TFP in the recalibrated model is well able to explain the two recessions in 1991 and 2008 (blue dashed dotted line). In particular, TFP now accounts for 4.7 percentage points of the 8.2 percent GDP drop during the Great Recession, compared to 2.6 percentage points reported in JQ.[3] While the model still misses the expansion in working hours as in JQ, TFP shocks now contribute 1.45 percentage points to the 4 percent volatility of hours, compared to the 0.96 percentage points reported in JQ. This is particularly visible during the Great Recession, where TFP shocks account for one quarter of the drop in hours instead of one eighth in

[1] The timing JQ use for capital in the construction of TFP is also inconsistent with the construction of financial conditions ξ_t, which relies on the beginning of period capital stock.

[2] The high correlation between the residuals could also indicate that the TFP and financial shocks do not represent structural shocks as assumed by JQ.

[3] This value increases to 6.1 percent when shutting off financial frictions, i.e. with $\kappa = \tau = 0$. See Figure C1 in the Appendix.

Figure 2. : Counterfactual model simulations

Note: The rows show the counterfactual GDP (left column) and hours (right column) obtained from the parsimonious model when simulating it with TFP shocks only (first row), financial shocks only (second row), and both shocks (third row). Green solid line: data; red dashed line: JQ results; blue dashed dotted line: recalibrated model. Shaded areas denote NBER recessions.

JQ. Regarding debt repurchases and equity payouts (Figure C1), TFP shocks cause larger movements, which is particularly visible during the Great Recession. TFP shocks are able to account for the full increase in debt repurchases, while predicting a decrease in equity payouts almost twice as big as in the data.

The middle row of Figure 2 displays the counterfactual series from the recalibrated model with financial friction residuals only. Looking at GDP, the fit is much less impressive than reported in JQ. The depth of the recession in 1991 is overpredicted, while the subsequent recovery and GDP peak occur too early. The GDP drop before and during the 2001 recession is also exaggerated compared to the data. During the 2008 recession a drop of 2.8 percent of

GDP is accounted for by the financial friction residual as opposed to the 4.4 percent drop reported in JQ. The model also misses the growth slowdown immediately before the Great Recession and instead predicts an expansion. At the end of the sample, the model predicts a very quick recovery, with GDP already being above its long-run mean when it was still 7.8 percent below trend in the data. The explanatory power of financial shocks for the movement of hours is still considerable. They can account for 2 percentage points of the 4 percent volatility, compared to 2.2 percentage points in JQ. However, during the Great Recession, the drop in hours due to financial residuals is 36 percent of the empirically observed drop, compared with more than half in JQ. The movements of debt repurchases and equity payouts (Figure C2) are generally similar compared to JQ, but with a slightly smaller amplitude.

Finally, the bottom row of Figure 2 shows the counterfactual series when both residuals enter the recalibrated model, thus incorporating the in-sample correlation between the residuals. The model accounts for 6.6 percentage points of the 8.2 percent output drop during the Great Recession, compared to 5.8 percentage points in JQ. The model is also better able to capture the expansion during the latter half of the 1990s, but this comes at the cost of more strongly overpredicting the expansion after the 2001 recession. The fit of hours is worse than reported in JQ, with both shocks now accounting for 5 instead of 6.1 percentage points of the 11.5 percent hours drop during the Great Recession. The volatility of hours over the whole sample is 1.8 percent, compared to 2.2 percent in JQ and 4 percent in the data. Turning to the financial variables (Figure C3), the counterfactual series are very similar to JQ, with the extreme peaks being slightly less pronounced. During the Great Recession, the model predicts an increase of debt repurchases of 12.0 instead of 12.9 percentage points, but this is still larger than the 8.9 percent increase in the data.

II. Extended model and structural estimation

This section is concerned with the medium-scale New Keyesian DSGE model of JQ. I first outline two issues with the estimation of this model in JQ before fixing them and reestimating the model.

A. Problems in JQ's model estimation

First order conditions

The technical appendix of JQ displays the equations of the extended model. However, there are three errors in the first order conditions for which I cannot ascertain whether they are simply typos or whether they also affect the model estimation (see Appendix A for details).

Reported posterior distribution

The estimation results in Table 3 of JQ suggest that the Metropolis-Hastings algorithm did not correctly sample from the posterior distribution. First, the highest posterior density intervals (HPDIs) are unusually narrow for the type of prior and sample length used. For example, Lawrence Christiano, Roberto Motto and Massimo Rostagno (2014) use a similar model, prior, and data length and report HPDIs that are wider by almost one order of magnitude. Second, although the posterior is known to be asymptotically normal (see Sungbae An and Frank Schorfheide, 2007, and the references therein), the posterior modes for parameters like the habit in consumption h (erroneously labelled λ in JQ's table 3) or the interest rate smoothing parameter ρ_R are outside of the 90 percent HPDIs. This is commonly a sign for parameter drift in the Markov Chain and for non-convergence.

B. Reestimating the model

Due to the errors in the first order conditions and the unusual posterior estimates reported, I reestimate the model on the original dataset with Bayesian techniques using Dynare (Stéphane Adjemian, Houtan Bastani, Fréderic Karamé, Michel Juillard, Junior Maih, Ferhat Mihoubi, George Perendia, Johannes Pfeifer, Marco Ratto and Sébastien Villemot, 2011).[4] Mode finding is conducted using the CMA-ES algorithm (Nikolaus Hansen, Sybille D. Müller and Petros Koumoutsakos, 2003), following the evidence of its good performance for global mode-finding in the context of DSGE models in Martin M. Andreasen (2010). The Monte Carlo Markov Chain consists of 10 millions draws from the Metropolis-Hastings algorithm

[4]As a practical matter, I formally target the debt-to-GDP ratio and the ratio of government spending to GDP in steady state by adjusting $\bar{G}$ and $\bar{\xi}$ for every draw of the parameters. This makes sure that the targets are still matched when the MCMC algorithm or the mode-finder vary parameters that affect the steady state like e.g. the average markups.

Table 1—: Posterior estimates with JQ prior

		Prior Distribution			Posterior Distribution			
					JQ	Reestimation		
Parameter Name	Par.	Dist	Mean	S.D.	Mode	Mode	5%	95%
Risk aversion	σ	norm	1.500	0.370	1.090	1.540	0.855	1.731
Frisch elasticity	ε	norm	2.000	0.750	1.761	0.873	0.940	2.998
Habit parameter	h	beta	0.500	0.300	0.608	0.367	0.263	0.500
Calvo Wage adjustment	ω	beta	0.500	0.300	0.278	0.075	0.037	0.220
Rotemberg price adjustment cost	ϕ	invg	0.100	0.300	0.031	6.997	7.300	29.584
Investment adjustment cost	ϱ	invg	0.100	0.300	0.021	0.149	0.102	1.371
Capital utilization cost	ψ	beta	0.500	0.150	0.815	0.775	0.548	0.882
Equity cost	κ	invg	0.200	0.100	0.426	0.287	0.254	0.935
Average price markup	$\bar{\eta}$	beta	1.200	0.100	1.137	1.806	1.712	1.871
Average wage markup	$\bar{\upsilon}$	beta	1.200	0.100	1.025	1.140	1.057	1.374
Productivity shock persistence	ρ_z	beta	0.500	0.200	0.902	0.920	0.864	0.949
Investment shock persistence	ρ_ζ	beta	0.500	0.200	0.922	0.913	0.623	0.928
Intertemporal shock persistence	ρ_γ	beta	0.500	0.200	0.794	0.949	0.920	0.979
Price markup shock persistence	ρ_η	beta	0.500	0.200	0.906	0.866	0.734	0.910
Wage markup shock persistence	ρ_υ	beta	0.500	0.200	0.627	0.981	0.945	0.996
Government shock persistence	ρ_G	beta	0.500	0.200	0.955	0.976	0.957	0.993
Interest policy shock persistence	ρ_ς	beta	0.500	0.200	0.203	0.213	0.131	0.338
Financial shock persistence	ρ_ξ	beta	0.500	0.200	0.969	0.990	0.978	0.998
Interaction production government	ρ_{gz}	beta	0.500	0.200	0.509	0.859	0.608	0.969
Taylor rule persistence	ρ_R	beta	0.750	0.100	0.745	0.784	0.767	0.849
Taylor rule feedback	ν_1	norm	1.500	0.250	2.410	2.202	1.984	2.505
Taylor rule feedback	ν_2	norm	0.120	0.050	0.000	-0.020	-0.032	0.050
Taylor rule feedback	ν_3	norm	0.120	0.050	0.121	0.176	0.141	0.232
Technology shock	σ_z	invg	0.001	0.050	0.005	0.005	0.004	0.005
Investment shock	σ_ζ	invg	0.001	0.050	0.006	0.009	0.007	0.049
Preference shock	σ_γ	invg	0.001	0.050	0.016	0.019	0.013	0.028
Price Markup shock	σ_η	invg	0.001	0.050	0.019	0.013	0.013	0.031
Wage Markup shock	σ_υ	invg	0.001	0.050	0.085	0.021	0.012	0.022
Government shock	σ_g	invg	0.001	0.050	0.028	0.016	0.014	0.018
Monetary shock	σ_ς	invg	0.001	0.050	0.002	0.001	0.001	0.002
Financial Shock	σ_ξ	invg	0.001	0.050	0.008	0.016	0.013	0.018

Note: norm: normal distribution; beta: beta distribution (generalized beta on [1,2] for markups); invg: inverse gamma distribution.

with a burn-in of 25 percent. The acceptance rate was 23 percent. Convergence of the Monte Carlo Markov Chain was visually checked via trace plots and formally using the John Geweke (1992) convergence diagnostics (see the technical appendix).

Table 1 displays the posterior estimation results. Most of the estimates are rather different than originally reported in JQ and more comparable to the previous literature.[5] At the

[5]This is potentially due to the posterior density being multimodal, with JQ presumably reporting a local instead of a global mode. The mode reported in Table 1 has a posterior density of 3080.90. During mode-finding, I encountered a second local mode with density 3078.22 that features parameter estimates and

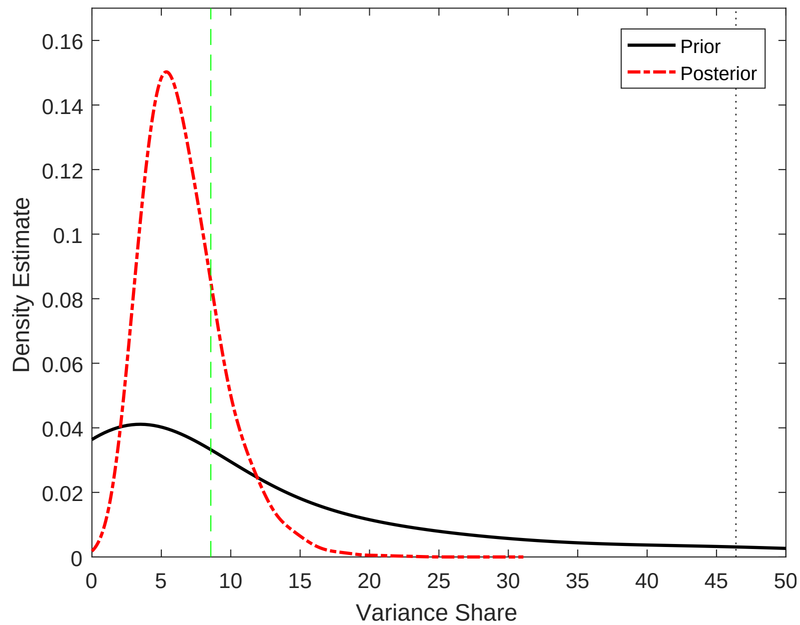


Figure 3. : Prior and posterior forecast error variance share of the financial shock ε_ξ in GDP growth rates in the reestimated model

Note: Kernel density estimate of the share of forecast error variance of GDP growth rates at horizon infinity explained by financial shocks ε_ξ; based on 10,000 draws from the prior (black solid line) and posterior (red dashed dotted line); green dashed line: variance share at the posterior mode of the reestimated model; black dotted line: posterior mean variance share reported in JQ.

same time, consistent with the previous literature, the HPDIs are considerably wider than originally reported in JQ. The Rotemberg price adjustment cost parameter ϕ is estimated at 7, almost 226 times bigger than in JQ and much closer to what e.g. Peter N. Ireland (2001) found. The implied price duration at the mode in a Calvo framework is 2.96 quarters compared to 1.004 in JQ. The capital adjustment cost parameter ϱ is estimated to be 0.15, between the value of 0.02 reported in JQ and the 2.48 reported in Lawrence J. Christiano, Martin Eichenbaum and Charles L. Evans (2005). While these values square better with the previous literature, the steady state price markup of 80 percent is much higher than typically found in estimated DSGE models (e.g. Alejandro Justiniano, Giorgio E. Primiceri and Andrea Tambalotti, 2013; David Altig, Lawrence Christiano, Martin Eichenbaum and Jesper Lindé, 2011), while the Calvo wage adjustment parameter of $\omega = 0.075$ is a lot lower.[6]

a variance decomposition rather similar to the one reported in JQ.

[6]The technical appendix, Section II reports estimation results with a more conventional Frank Smets and Rafael Wouters (2007)-type prior. While this prior induces more plausible posterior parameter estimates, the results on the business cycle contribution of financial shocks are very similar to the ones obtained with the JQ prior.

Table 2—: Posterior forecast error variance decomposition (in percent) at horizon infinity in the reestimated model

	TFP shock ε_z	MEI shock ε_ζ	Intert. shock ε_γ	Price MK shock ε_η	Wage MK shock ε_υ	Govern. shock ε_g	Money shock ε_ς	Fin. shock ε_ξ	Fin. shock ε_ξ
	Reestimation								JQ
GDP	5.99	26.11	8.06	25.36	11.63	5.96	10.36	6.53	46.4
Consumption	4.33	23.27	20.81	8.85	24.66	5.95	7.56	4.57	0.6
Investment	1.98	74.45	5.97	11.08	2.68	0.10	2.39	1.35	24.7
Inflation	3.98	18.09	18.60	17.88	8.37	0.70	12.69	19.69	9.5
FF rate	1.24	53.30	31.64	4.16	5.68	1.53	1.09	1.36	4.7
Hours	22.42	26.15	3.69	14.52	17.36	6.74	5.95	3.17	33.5
Wages	2.13	4.98	15.45	21.51	36.78	1.52	8.15	9.48	1.0
Debt repayments	4.05	38.51	5.30	16.80	7.77	0.83	2.44	24.32	13.5

Note: Average over 10,000 draws from the posterior distribution of the reestimated model. All variables are in growth rates, except for the federal funds rate and the share of debt repurchases to GDP, which are in levels. The last column displays the results for financial shocks reported in JQ.

The higher price and investment adjustment cost estimates change the conclusions derived from the model. Figure 3 displays the prior and posterior kernel density estimates of the forecast error variance share of GDP growth rates at horizon infinity explained by the financial shock ε_ξ. While the prior density is rather diffuse and includes high variance shares, the posterior mass is concentrated at values below 15 percent. Table 2 reports the posterior mean variance decomposition for the observables. In the reestimated model, the financial shock ε_ξ is on average responsible for less than 7 percent of output fluctuations, as opposed to the 46 percent originally reported in JQ. Price markup and MEI shocks[7] now account for most of GDP growth rate fluctuations. Similarly, the variance share of hours explained is 3 percent compared to 34 percent in JQ. However, financial shocks now play a larger role for explaining the forecast error variance of inflation and debt repurchases.

Figure 4 displays the historical shock decomposition from the reestimated model, corresponding to JQ's Figure 10. Consistent with the small role of the financial shock in the unconditional forecast error variance decomposition, the historical GDP movements explained

[7]While JQ term this shock "investment-specific technology shock", it does not empirically map into the relative price of investment and has subsequently become known as a "marginal efficiency of investment" shock (see Justiniano, Primiceri and Tambalotti, 2011) to distinguish it from the Jonas D.M. Fisher (2006) investment-specific technology shock that empirically maps into the relative price of investment.

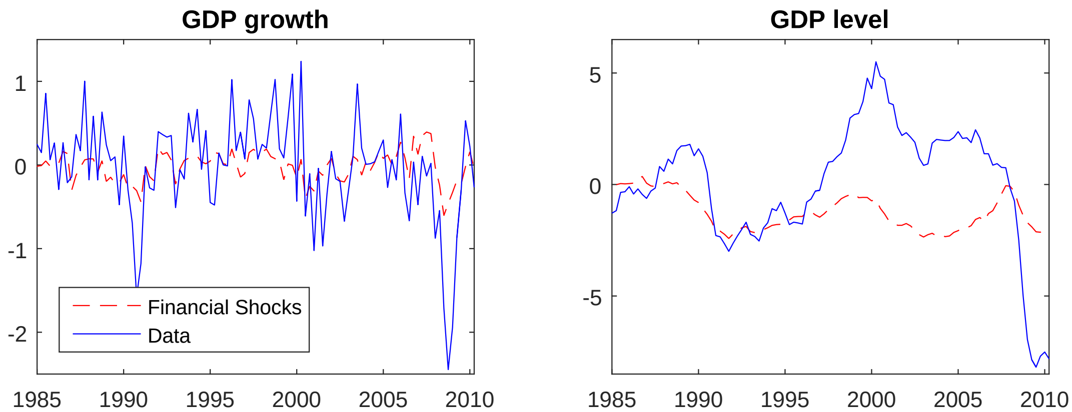


Figure 4. : Responses of the extended model to the financial shock ε_ξ with parameters set to the posterior mode.

Note: Left panel: Data growth rates (blue solid line) are demeaned, growth rates implied by financial shocks (red dashed line) are derived from a historical shock decomposition; Right panel: data depicted is linearly detrended log GDP (blue solid line), level implied by financial shocks (red dashed line) results from cumulated growth rates

by financial shocks are small. During the Great Recession, financial shocks account for close to 2 percentage points of the 8.2 percent GDP drop during the Great Recession, compared to almost half in JQ.

III. Conclusion

Considered jointly, the evidence from the parsimonious model with the corrected TFP measure and the reestimated, corrected medium-scale model suggests that the particular type of microfounded financial shocks advocated in JQ are not an important driver of U.S. business cycle fluctuations, except during selected periods. This does not necessarily imply that financial frictions and financial shocks in general do not play a central role in explaining macroeconomic fluctuations. As noted in Justiniano, Primiceri and Tambalotti (2011), the MEI shock, which turns out to be the most important driver of output fluctuations in the reestimated extended model, can be interpreted as a "proxy for the effectiveness with which the financial sector channels the flow of household savings into new productive capital." In fact, it tends to be highly correlated with measures of stress in financial markets like the credit spread between high yield and AAA bonds. The challenge consists of providing credible microfoundations for this type of time-varying friction.

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PROBLEMATIC FIRST ORDER CONDITIONS

First, in the capital utilization FOC, equation (2) of JQ's Technical Appendix,

$$(1-\mu_t\varphi_{d,t})F_{u,t}-\Psi_{u,t}k_t\varphi_{d,t}-\chi_t D_{u,t}\varphi_{d,t}=0 \tag{JQ-App. 2}$$

there should be no $\varphi_{d,t}$ attached to the second term $\Psi_{u,t}k_t$:

$$(1-\mu_t\varphi_{d,t})F_{u,t}-\Psi_{u,t}k_t-\chi_t D_{u,t}\varphi_{d,t}=0\,. \tag{A1}$$

To see this, consider the relevant parts of the firm's Lagrangian:

$$\lambda_t P_t\left(\left[F\left(u_t\right)-\Psi\left(u_t\right)k_t\right]+\ldots\right)+\mu_t\left(-F\left(u_t\right)+\ldots\right)+\chi_t\left(-D\left(u_t\right)+\ldots\right) \tag{A2}$$

Taking the derivative with respect to u_t and setting it to 0 results in the first order condition:

$$\lambda_t P_t\left(F_{u,t}-\Psi_{u,t}k_t\right)-\mu_t F_{u,t}-\chi_t D_{u,t}=0\,, \tag{A3}$$

where $\lambda_t P_t$ can be eliminated using the condition $\lambda_t P_t=\varphi_{d,t}^{-1}$. Equation (A3) shows that the $\Psi_{u,t}k_t$ term has the same prefactor as the first $1\times F_{u,t}$ part of the term $(1-\mu_t\varphi_{d,t})F_{u,t}$ in (JQ-App. 2), resulting in equation (A1).

Second, in the Euler equation for capital, equation (3) of JQ's technical appendix,

$$E_t m_{t+1}\left\{(1-\delta)Q_{t+1}+\frac{F_{k,t+1}-\Psi_t}{\varphi_{d,t+1}}-\mu_{t+1}F_{k,t+1}-\chi_{t+1}D_{k,t+1}\right\}+\xi_t\mu_t-Q_t=0 \tag{JQ-App. 3}$$

the capacity utilization term Ψ_t within the conditional expectations should be dated Ψ_{t+1}:

$$E_t m_{t+1}\left\{(1-\delta)Q_{t+1}+\frac{F_{k,t+1}-\Psi_{t+1}}{\varphi_{d,t+1}}-\mu_{t+1}F_{k,t+1}-\chi_{t+1}D_{k,t+1}\right\}+\xi_t\mu_t-Q_t=0 \tag{A4}$$

The third error refers to the definition of debt repurchases as a share of GDP x_t, equation

(17) of JQ's technical appendix,

$$x_t = \frac{\frac{b_t}{1+r_{t-1}} - \frac{b_{t+1}}{1+r_t}}{Y_t}, \tag{JQ-App. 17}$$

where b_t are nominal bonds and Y_t is real GDP. As JQ match x_t to data on nominal debt repurchases as a share of nominal gross value added in the private business sector, real GDP Y_t in the model must be multiplied by the price level P_t to obtain nominal GDP in the denominator. The correct equation reads:

$$x_t = \frac{\frac{b_t}{1+r_{t-1}} - \frac{b_{t+1}}{1+r_t}}{Y_t\, P_t} \tag{A5}$$

There are two additional typos in the published paper. The Taylor rule, equation (28), should read:

$$\frac{1+r_t}{1+\bar{r}} = \left(\frac{1+r_{t-1}}{1+\bar{r}}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\bar{\pi}}\right)^{\nu_1} \left(\frac{Y_t}{Y_t^*}\right)^{\nu_2}\right]^{1-\rho_R} \left(\frac{\frac{Y_t}{Y_t^*}}{\frac{Y_{t-1}}{Y_{t-1}^*}}\right)^{\nu_3} \varsigma_t$$

to be consistent with equation (16) of JQ's Technical Appendix and Smets and Wouters (2007). Moreover, it must be that $\vartheta = \frac{1-\bar{\xi}\bar{\mu}}{\beta} - (1-\delta)$ for capacity utilization u to be 1 in steady state.

Recalibration of the parsimonious model and model IRFs

JQ set the dividend adjustment cost parameter κ in their model to target the historical volatility of the equity payout to GDP series, d/y. However, when simulating the model with the corrected BGVA-TFP and the dividend adjustment cost parameter set at $\kappa = 0.146$ as in JQ, the volatility of the simulated equity payout series is only 1 percent compared to 1.2 percent in the data. The reason is that when using the same sectoral output concept to construct financial conditions and TFP, the shocks from the VAR in (1) are more strongly correlated than in JQ (0.74 as opposed to 0.55). Figure B1 reproduces Figure 6 of JQ for the recalibrated parsimonious model. The model IRFs show that negative TFP shocks lead to an increase in equity payouts, while negative financial shocks lead to a decrease. A stronger positive correlation between shocks in the historical sample therefore implies that these two effects offset each other more frequently, reducing the overall volatility of the equity payout

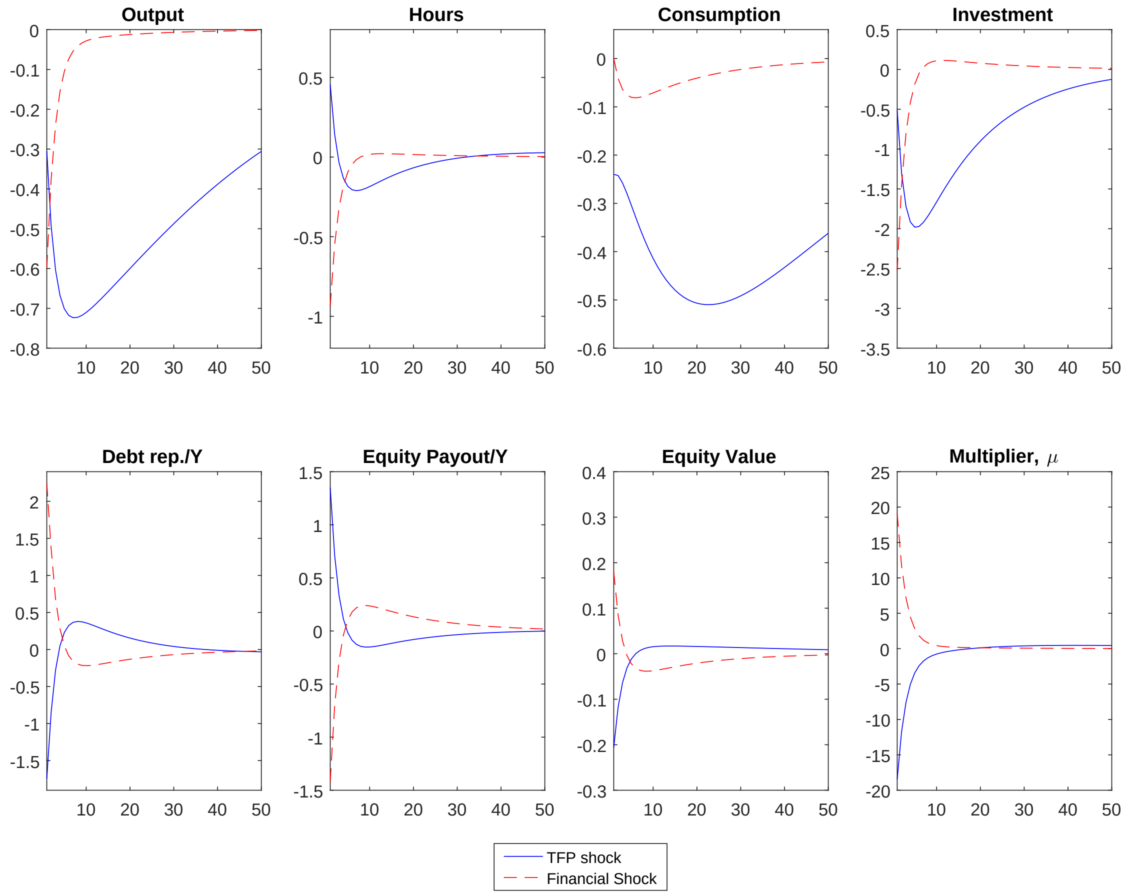

Figure B1. : Impulse Responses to structural shocks in the recalibrated parsimonious model

Note: IRFs to negative one standard deviation TFP (blue solid line) and financial shocks (red dashed line) from the parsimonious model recalibrated with a dividend adjustment cost parameter of $\kappa = 0.08$. x-axis: quarters, y-axis: percentage deviation from steady state. As in JQ, IRFs are generated with off-diagonal elements of $\mathbf{A}$ in equation (1) set to 0.

to GDP ratio predicted by the model. Increasing the volatility of d/y to the level found in the data requires reducing the equity adjustment cost parameter κ to 0.08.

Counterfactual series from the recalibrated parsimonious model

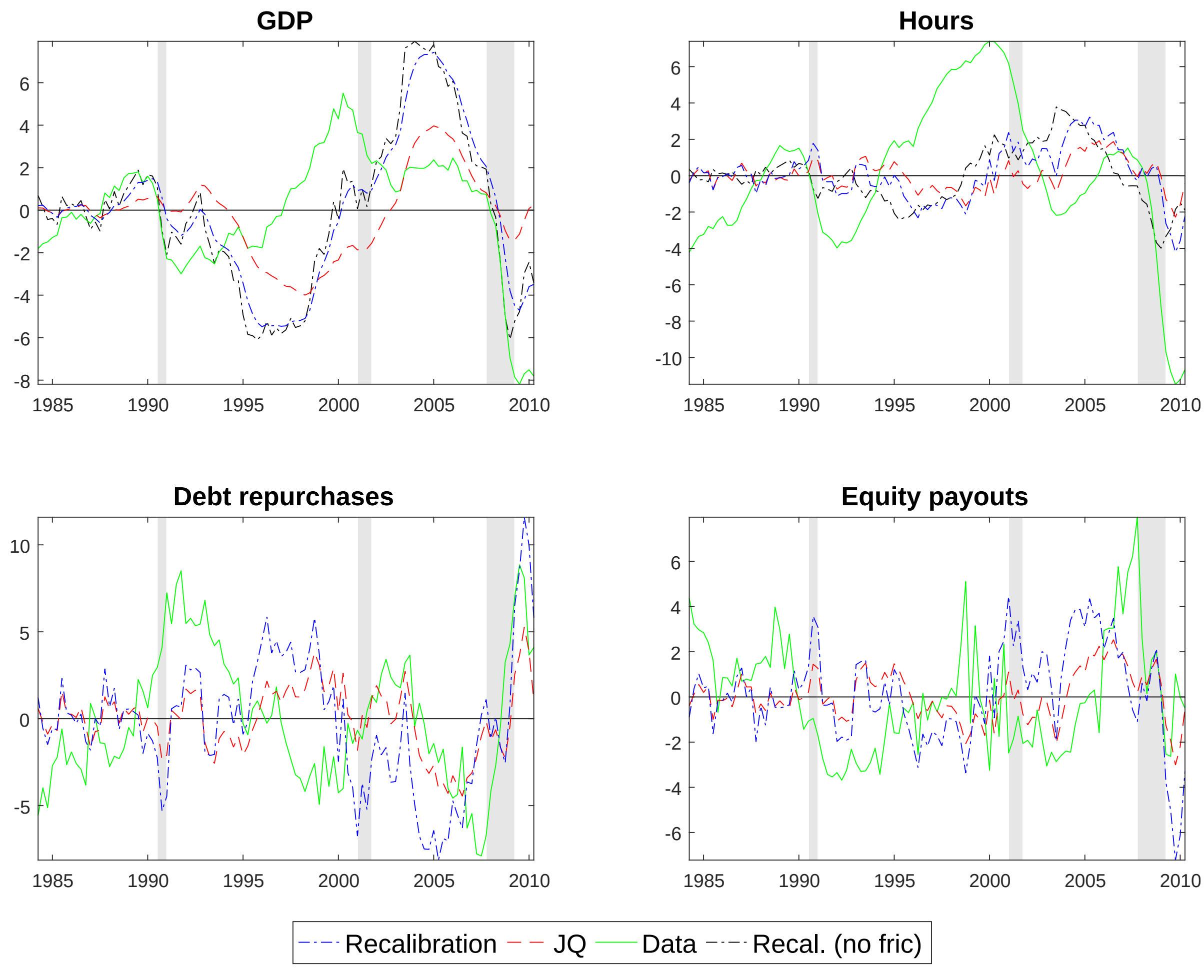

Figure C1. : Response to TFP residual only

Note: Counterfactual GDP (top left), hours (top right), debt repurchases (bottom left), and equity payout (bottom right) series obtained from the parsimonious model when simulating it with TFP shocks only. Green solid line: data; red dashed line: JQ results; blue dashed dotted line: recalibrated model with financial frictions; black dashed dotted line: recalibrated model without financial frictions. Shaded areas denote NBER recessions.

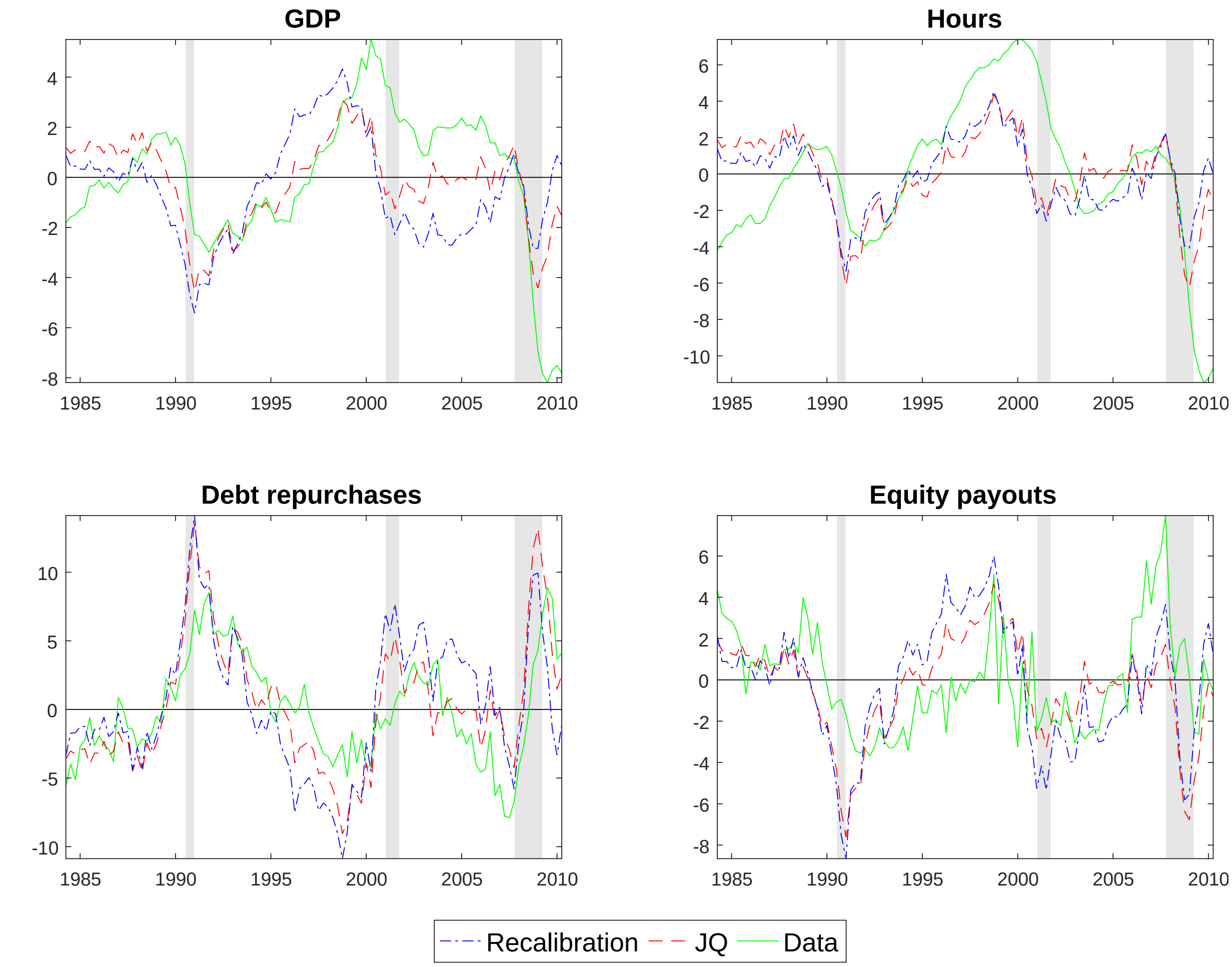

Figure C2. : Response to financial residual only

Note: Counterfactual GDP (top left), hours (top right), debt repurchases (bottom left), and equity payout (bottom right) series obtained from the parsimonious model when simulating it with financial shocks only. Green solid line: data; red dashed line: JQ results; blue dashed dotted line: recalibrated model. Shaded areas denote NBER recessions.

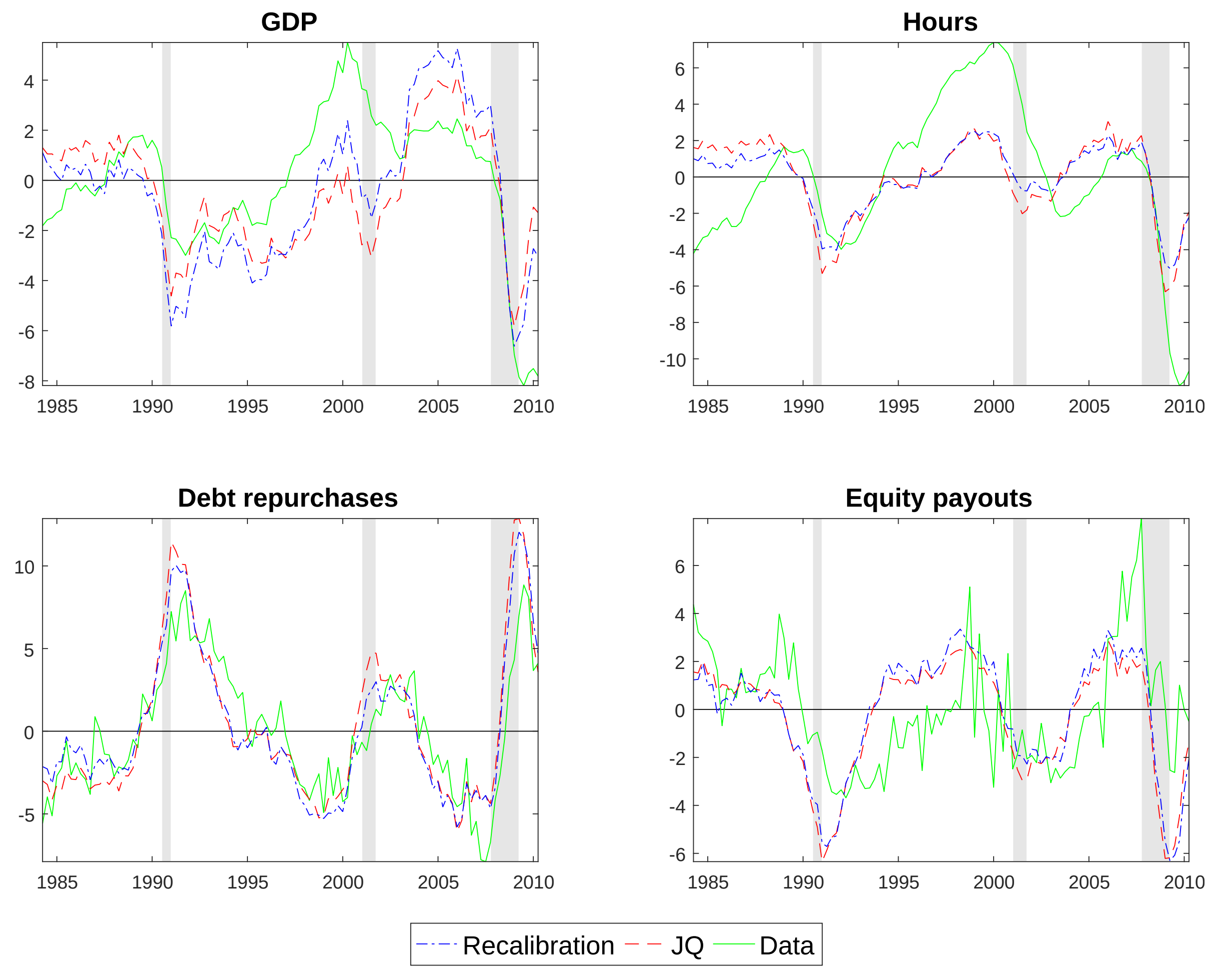

Figure C3. : Response to both residuals

Note: Counterfactual GDP (top left), hours (top right), debt repurchases (bottom left), and equity payout (bottom right) series obtained from the parsimonious model when simulating it with both shocks. Green solid line: data; red dashed line: JQ results; blue dashed dotted line: recalibrated model. Shaded areas denote NBER recessions.