Animal Spirits, Financial Markets and Aggregate Instability*

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Abstract

People's psychological motivations are a significant contributor to the fluctuations of the U.S. business cycle. This insight is demonstrated within an estimated artificial economy with financial market frictions. Animal spirits shocks account for around 40 percent of output fluctuations over the period from 1955 to 2014. Financial friction and technology shocks are considerably less important with best point estimates for both near 20 percent.

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1 Introduction

This paper presents evidence on the sources of business cycles for the post-Korean War American economy. Our results support the view that people's psychological motivations, aka animal spirits, have played a significant part in the ups and downs of the U.S. aggregate economic activity. In fact, animal spirits have caused around 40 percent of output volatility. This insight is demonstrated within an artificial economy with financial market frictions. Furthermore, the exercise suggests that the 2007-2009 recession was chiefly caused by an tightening of firms' financing conditions.

Models with credit market frictions have become popular since the Great Recession. This interest reflects the often stated view that disruptions to financial markets were the factors that pulled down the world economy in 2008. Building on earlier work, such as Kiyotaki and Moore (1997) and Bernanke, Gertler and Gilchrist (1999), this research shows how financial market frictions can amplify shocks to macroeconomic fundamentals by transforming small economic disturbances into large business cycles. Del Negro, Giannoni and Schorfheide (2015), for example, extend a medium scale New Keynesian model by financial market frictions to explain some key aspects of the Great Recession.[1]

We depart from the aforementioned works twofold. First, we allow for non-fundamental disturbances to potentially cause business cycles, that is, we open up the parametric space of the model to include multiple equilibria. Second, unlike most existing work on such indeterminacy, we concentrate on estimating the model and focus on the empirical implications of the multiplicity by explicitly analyzing the business cycle variance contribution of animal spirits or belief shocks. The undertaking is implemented by building on a variant of Benhabib and Wang (2013). Indeterminacy in this model is linked to a countercyclical tightening of financial market frictions, a phenomena that receives support empirically. As will be discussed later, the spread between Baa corporate bonds and the ten-year US government bond rate is a relevant instrument for financial market conditions and Figure 1 shows that these conditions are more relaxed in times of booms. In the artificial economy, the interaction of time varying collateral constraints and a coun-

[1] See also Nolan and Thoenissen (2009).

tercyclical markup spawns equilibrium indeterminacy – fluctuations are driven by changes to people's animal spirits. The economy is subjected to a parade of fundamental shocks that all have been identified as important drivers of business cycles as well as of belief shocks. The model is estimated by full information Bayesian methods using quarterly U.S. data covering the 1955:I-2014:IV period. This approach follows various key contributions by Otrok (2001), Justiniano, Primiceri and Tambalotti (2011) and Schmitt-Grohé and Uribe (2012), who all, however, only explore the role of fundamental shocks as engines of business cycles.

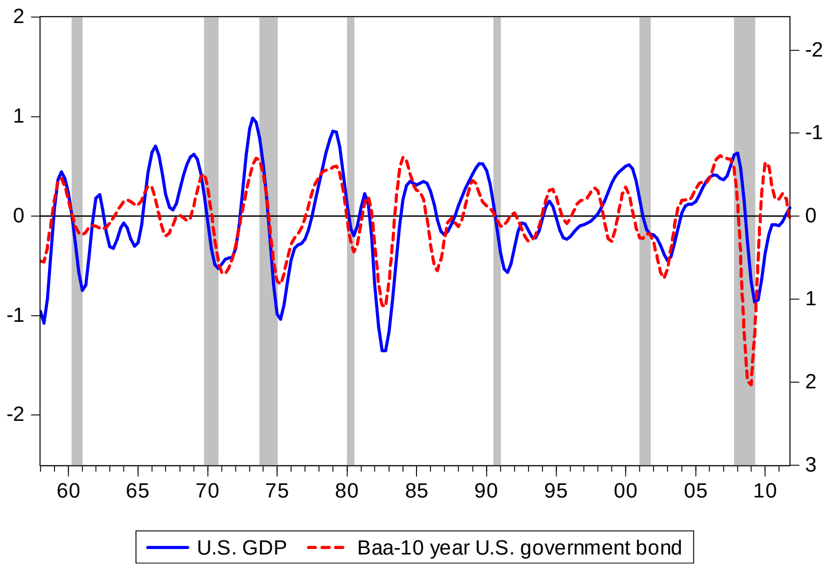

Figure 1: U.S. GDP and credit spread (on right-hand scale)

The Bayesian estimation chooses shocks so that the probability of the observed series is maximized and the key result that transpires from this exercise is that animal spirits are important factors to the U.S. economy and these shocks are responsible for a significant portion of its macroeconomic fluctuations. Specifically, by computing forecast error variance decompositions, we find that animal spirits account for well in excess of one third of U.S. output variations and about half of fluctuations in investment. Thus, we find a significantly larger role for belief shocks than Pintus, Wen and Xing (2015). Disturbances that originate in the financial sector explain less than twenty percent of output fluctuations. Only in the case of the Great Recession can the case be made that financial factors played a significant role. Hence, in some sense, business cycles are not all alike.

2 Baseline Model

The artificial economy is a discrete-time adaptation of Benhabib and Wang (2013). The model features credit frictions in the form of endogenous borrowing constraints in a model of monopolistic competition in which, as usual, perfectly competitive firms produce final output by combining a continuum of differentiated intermediate inputs. Intermediate good producing firms are collateral constrained in how much they can borrow to finance their working capital needs. We modify the original model by incorporating a set of fundamental shocks which are widely considered as key drivers of business cycles. The model's discussion will be brief and it will concentrate on the alterations from the original version.

2.1 Technology

A unit mass of monopolistic competitive firms has access to a constant returns technology that transforms capital services $\kappa_t(i)$ and labor hours $N_t(i)$ into intermediate, differentiated outputs $Y_t(i)$

$$Y_t(i) = \kappa_t(i)^{\alpha}(X_t N_t(i))^{1-\alpha} \qquad 0 < \alpha < 1.$$

Exogenous labor-augmenting technological progress X_t affects all firms equally. Its growth rate $\mu_t^x \equiv X_t/X_{t-1}$ evolves as a first-order autoregressive process

$$\ln \mu_t^x = (1-\rho_x)\ln \mu^x + \rho_x \ln \mu_{t-1}^x + \varepsilon_{x,t} \qquad 0 < \rho_x < 1$$

with $\varepsilon_{x,t} \backsim N(0, \sigma_x^2)$ and $\ln \mu^x$ is average growth rate. Factor services are rented from the households at perfectly competitive prices W_t and r_t. Final output Y_t is a constant elasticity of substitution aggregator of a basket of intermediate inputs

$$Y_t = \left(\int_0^1 Y_t(i)^{\frac{\lambda-1}{\lambda}} di\right)^{\frac{\lambda}{\lambda-1}} \qquad \lambda > 1.$$

Here λ denotes the elasticity of substitution between varieties. The monopolistic competitive firms generate profits by marking up prices over marginal costs. They must borrow for working capital needs. Imperfect enforcement requires a process to constrain borrowing by the value of the collateral. Specifically, firm i's total amount of debt is an intraperiod loan $B_t(i)$

$$B_t(i) = W_t N_t(i) + r_t \kappa_t(i)$$

and it is constrained by the value of the collateral, which is the output being produced, i.e.

$$W_t N_t(i) + r_t \kappa_t(i) \leq \xi_t P_t(i) Y_t(i).$$

ξ_t reflects the tightness of the credit market. Under this credit constraint, if there is a default event, the lender has the right to recover a fraction ξ_t of less than one of the firm's end-of-period value of output $P_t(i)Y_t(i)$.[2] Concretely, ξ_t refers to the extent of the borrowing limit and it stands in as an endogenous credit constraint: the borrowing tightness varies with the aggregate state of economic activity which reflects creditors' ability to pay back loans. In particular, ξ_t is an increasing and convex function of the deviation of actual output from balanced growth output:

$$\xi_t = \frac{1}{\tau} \left(\frac{Y_t}{\overline{Y}_t} \right)^{\frac{\tau}{\omega}}$$

with parameter restrictions $0 < \frac{1}{\tau} < 1$ and $\omega > 0$. We see this formulation of ξ_t a general way to capture many more specific models. For example, it can stand in for Benhabib and Wang's (2014) original setup with fixed liquidation costs. Figure 1 suggests that empirically conditions on financial markets are indeed countercyclical. The corresponding first-order conditions for the profit maximization problem involve

$$r_t \kappa_t(i) = \alpha \phi_t Y_t(i)$$

$$W_t N_t(i) = (1 - \alpha) \phi_t Y_t(i)$$

and

$$\frac{\lambda - 1}{\lambda} P_t(i) - \phi_t + \mu_t(i) \left[\xi_t \frac{\lambda - 1}{\lambda} P_t(i) - \phi_t \right] = 0 \tag{1}$$

[2]Unlike the original model, our setup does not include fixed liquidation costs. Indeterminacy still holds. When we compare the two models using Bayesian estimation method, we find that the model without fixed costs is favored by the data.

where $\mu_t(i)$ denotes the multiplier associated with the borrowing constraint and ϕ_t stands for monopolistic firms' marginal costs.

2.2 Preferences

Households are represented by an agent with the lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\ln(C_t - \Delta_t) - \varphi \frac{N_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} \right) \qquad 0 < \beta < 1,\ \eta > 0 \text{ and } \varphi > 0$$

where β is the discount factor, C_t stands for consumption, and N_t for total hours worked. The functional form of the period utility ensures that the economy is consistent with balanced growth. The parameter η measures the Frisch elasticity of substitution for labor supply and φ denotes the disutility of working. The term Δ_t represents shocks to the agent's utility of consumption that generate urges to consume, as in Baxter and King (1991) and Weder (2006). The preference shock follows the autoregressive process

$$\ln \Delta_t = \rho_\Delta \ln \Delta_{t-1} + \varepsilon_{\Delta,t} \qquad 0 < \rho_\Delta < 1$$

with $\varepsilon_{\Delta,t} \backsim N(0, \sigma_\Delta^2)$. This shock drives the economy's labor wedge, i.e. the gap between the marginal rate of consumption-leisure substitution and the marginal product of labor. Hence, our estimation will allow a much wider interpretation than mere shocks to preferences – a more agnostic reading would include, for example, changes to monetary policy, taxes, or labor market frictions. Households own the physical capital stock K_t and decide on its utilization rate, u_t, thus $\kappa_t = u_t K_t$. The agent faces the period budget constraint

$$C_t + A_t I_t + T_t = W_t N_t + r_t u_t K_t + \Pi_t$$

and the law of motion for capital is

$$K_{t+1} = (1 - \delta_t) K_t + I_t$$

The term I_t is investment spending and A_t represents a non-stationary investment-specific technology shock which affects the transformation of consumption goods into investment goods. In the model, the concept corresponds to the relative price of new investment goods in terms of consumption goods. The shock's growth rate μ_t^a evolves as

$$\ln \mu_t^a = (1-\rho_a)\ln \mu^a + \rho_a \ln \mu_{t-1}^a + \varepsilon_{a,t} \qquad 0 < \rho_a < 1$$

with $\varepsilon_{a,t} \backsim N(0, \sigma_a^2)$, and $\ln \mu^a$ is the average growth rate. Lump-sum taxes are denoted by T_t. The rate of physical capital depreciation

$$\delta_t = \delta_0 \frac{u_t^{1+\nu}}{1+\nu} \qquad 0 < \delta_0 < 1 \text{ and } \nu > 0$$

is an increasing function in the utilization and $\nu > 0$ measures the elasticity of the depreciation rate with respect to capacity used. The first-order conditions are standard and delegated to the Appendix.

2.3 Government

The government purchases G_t units of the final output. G_t is neither productive nor does it provide any utility. The spending is financed by the lump-sum taxes. We model government's spending with a stochastic trend

$$X_t^G = (X_{t-1}^G)^{\psi_{yg}}(X_{t-1}^Y)^{1-\psi_{yg}} \qquad 0 < \psi_{yg} < 1$$

where ψ_{yg} governs the smoothness of the government spending trend relative to the trend in output. Then, detrended government spending is $g_t \equiv G_t/X_t^G$ and this follows the process

$$\ln g_t = (1-\rho_g)\ln g + \rho_g \ln g_{t-1} + \varepsilon_{g,t} \qquad 0 \leq \rho_g < 1$$

with the shock's variance σ_g^2.

2.4 Equilibrium

In symmetric equilibrium, $\kappa_t(i) = u_t K_t$, $N_t(i) = N_t$, $P_t(i) = P_t = 1$, $Y_t(i) = Y_t$ and $\Pi_t(i) = \Pi_t = Y_t - W_t N_t - r_t u_t K_t$, hold and (1) becomes

$$\frac{\lambda - 1}{\lambda} - \phi_t + \mu_t \left[\xi_t \frac{\lambda - 1}{\lambda} - \phi_t \right] = 0. \tag{2}$$

From (2), and if $\xi_t \frac{\lambda-1}{\lambda} < \phi_t < \frac{\lambda-1}{\lambda}$, the financial constraint binds, thus,

$$\phi_t = \xi_t = \frac{1}{\tau} \left(\frac{Y_t}{\bar{Y}_t} \right)^{\frac{\tau}{\omega}}.$$

2.5 Self-fulfilling dynamics

> "The self-fulfilling prophecy is, in the beginning, a false definition of the situation evoking a new behavior which makes the originally false conception come true." [Merton, 1948]

The detrended and linearized economy is solved numerically (using standard parameters as listed in Table 1) and local dynamical regions can be formed by varying the marginal costs (i.e. the inverse of the markup) and the curvature parameter ω of the borrowing limit function. Figure 2 maps the dynamics' zones in the $\phi - \omega-$space. If market power is small, i.e. $\phi \to 1$ and the credit limit is constant i.e. $\omega \to \infty$ the economy's dynamics are unique. However, a combination of market power, i.e. $\phi < 1$, and a procyclical credit limit ξ_t delivers indeterminacy. The indeterminacy mechanism operates via an upwardly sloping wage-hours locus similar to many animal spirits models. Then, how can pessimistic expectations about the future create problems? If people believe that the future is worse, they will attempt to work more hours. In terms of the labor market equilibrium, this change in expectations will shift the labor supply curve out. But the pessimistic expectations will lead households to decrease the lending to firms. This contraction of credit will tighten the firms' borrowing constraints; markups will rise and the individual labor demand schedules move leftwards. As a consequence, the economy's wage-hours-locus is upwardly sloping. In equilibrium, the outward shift of labor supply will result in lower employment, in a drop in aggregate production and the low animal spirits will be self-fulfilling.

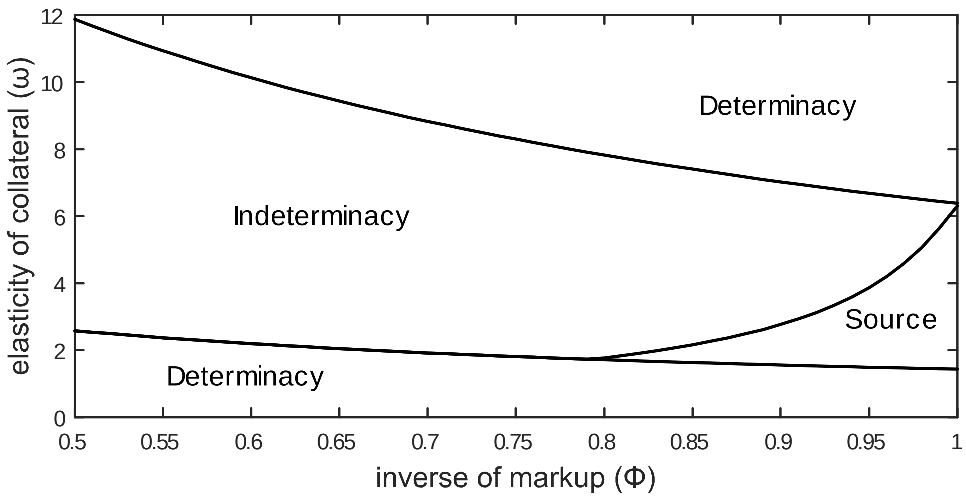

Figure 2: Parameter space for dynamics.

3 Estimation

> "We don't understand why and how we have recurrent business cycles but there's always a lot of talk about how to understand them." [Arrow, 2009]

As we have seen, the artificial economy's local dynamics can become indeterminate. Our next step discusses how animal spirits are introduced into the model, present the data that is employed in the analysis, as well as the full information Bayesian estimation of the artificial economy. Finally, we compare the estimated shocks to corresponding empirical measures.

If there are many rational expectations equilibria in the model economy, this continuum is a device to introduce animal spirits (see Farmer, Khramov and Nicolò, 2015). To do this, we break down the forecast error of output

$$\eta_t^y \equiv \hat{y}_t - E_{t-1}\hat{y}_t$$

into fundamental and non-fundamental components, as suggested by Lubik and Schorfheide (2003):

$$\eta_t^y = \Omega_x \varepsilon_t^x + \Omega_a \varepsilon_t^a + \Omega_\Delta \varepsilon_t^\Delta + \Omega_g \varepsilon_t^g + \varepsilon_t^b.$$

The parameters Ω_x, Ω_a, Ω_Δ and Ω_g determine the effect of permanent technology, investment-specific technology, preference and government spending shocks on the expectations error. This break-down leaves the belief shock ε_t^b as a residual. The last equation promulgates a strict definition of animal spirits: they are orthogonal to the other disturbances, thus independent of economic fundamentals (see Pavlov and Weder, 2017).

We now estimate the model, allowing all five shocks to matter. The approach allows us to attribute the contribution of each shock to aggregate fluctuations. The estimation uses quarterly U.S. data running from 1955:I to 2014:IV and includes six observable time series: the log difference of real per capita GDP, real per capita consumption, real per capita investment, real per capita government spending, the relative price of investment, as well as the log difference of per capita hours worked from its sample mean. The Appendix provides a full description of the data and its construction. The corresponding measurement equation is

$$\begin{bmatrix} \ln Y_t - \ln Y_{t-1} \\ \ln C_t - \ln C_{t-1} \\ \ln A_t I_t - \ln A_{t-1} I_{t-1} \\ \ln G_t - \ln G_{t-1} \\ \ln A_t - \ln A_{t-1} \\ \ln N_t - \ln \bar{N} \end{bmatrix} = \begin{bmatrix} \hat{y}_t - \hat{y}_{t-1} + \hat{\mu}_t^y \\ \hat{c}_t - \hat{c}_{t-1} + \hat{\mu}_t^y \\ \hat{\imath}_t - \hat{\imath}_{t-1} + \hat{\mu}_t^y \\ \hat{g}_t - \hat{g}_{t-1} + \hat{a}_t^g - \hat{a}_{t-1}^g + \hat{\mu}_t^y \\ \hat{\mu}_t^a \\ \hat{N}_t \end{bmatrix} + \begin{bmatrix} \ln \mu^y \\ \ln \mu^y \\ \ln \mu^y \\ \ln \mu^y \\ \ln \mu^a \\ 0 \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t}^{me} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where $a_t^g \equiv X_t^G / X_t^Y = (a_{t-1}^g)^{\psi_{yg}} (\mu_t^y)^{-1}$. Output growth is measured with an error $\varepsilon_{y,t}^{me}$ which is an i.i.d. innovation with mean zero and standard deviation σ_y^{me}. The measurement error is restricted to absorb not more than ten percent of the variance of output growth. We implement Dynare to estimate the model.

Prior to the estimation, a number of parameters are fixed. This set of parameters is calibrated following the literature and is usually based on national accounts data averages. We thus only address some of these calibrations (listed in comple-

Table 1: Calibration

Parameter	Values	Description
β	0.99	Subjective discount factor
α	1/3	Capital share
η	∞	Labor supply elasticity
λ	10	Elasticity of substitution
δ	0.0333	Steady-state depreciation rate
u	1	Steady-state capacity utilization rate
$\bar{G}/\bar{Y}$	0.21	Steady-state government expenditure share of GDP
μ^y	1.0041	Steady-state gross per capita GDP growth rate
μ^a	0.9949	Steady-state gross growth rate of price of investment

tion in Table 1). The elasticity of substitution parameter λ is set at ten, as in Dotsey and King (2005) and Cogley and Sbordone (2008). The average government spending share in GDP, $\bar{G}/\bar{Y}$, is calibrated at 21 percent, a number which we take from national accounts. The quarterly growth rates of per capita output μ^y and the relative price of investment μ^a are set equal their sample averages of 1.0041 and 0.9949. Finally, the household's first-order conditions determine the elasticity of the depreciation rate via $\nu = (\mu^k/\beta - 1)/\delta$.

The other model parameters are estimated. Our prior assumptions are summarized in Table 2. The parameters estimated here include the steady state marginal cost ϕ, the elasticity of collateral ω, the parameters that describe the stochastic processes and the standard deviation of the measurement error. A beta distribution is adopted for the steady-state marginal cost ϕ and its value falls between 0.83 and 0.9, so that the steady-state markup varies from around 11 to 20 percent. The range of marginal costs is chosen for two reasons. First, the empirically estimated markup falls in this range (see for example Cogley and Sbordone, 2008). Second, the upper bound value of ϕ is further restricted by the inequality constraints $\xi\frac{\lambda-1}{\lambda} < \phi < \frac{\lambda-1}{\lambda}$ for indeterminacy to arise.[3] We assume that the autocorrelations follow a beta distribution, that the standard deviations of the shocks follow an

[3]To land in the prior region of ω, we calculate the required region of ω to generate indeterminacy given each value of ϕ, as shown in Figure 1. We choose the minimum value 1.984 as the lower bound of the prior region, while 7.566 is the upper limit. This range will guarantee that we can cover the complete indeterminacy region. Since our model is indeterminate, during the MCMC, all proposed draws from determinacy or source region were discarded.

inverse gamma distribution. The prior distribution for the expectational parameters Ω_x, Ω_a, Ω_Δ and Ω_g is uniform indicating that we are agnostic about their values. We use endogenous priors to prevent overpredicting the model variances (see Christiano, Trabandt and Walentin, 2011).

Table 2: Estimation

	Prior distribution		Posterior distribution	
Estimated parameters	Range	Density [mean,std]	Mean	90% Interval
Steady-state marginal cost, ϕ	[0.83,0.90]	Beta [0.88,0.01]	0.833	[0.831,0.834]
Elasticity of collateral, ω	[1.984,7.566]	Uniform	3.464	[3.380,3.547]
Gov. trend smoothness, ψ_{yg}	[0,1)	Beta [0.5,0.2]	0.973	[0.962,0.984]
AR technology shock, ρ_x	[0,1)	Beta [0.5,0.2]	0.037	[0.015,0.059]
AR investment shock, ρ_a	[0,1)	Beta [0.5,0.2]	0.037	[0.018,0.056]
AR preference shock, ρ_Δ	[0,1)	Beta [0.5,0.2]	0.986	[0.983,0.989]
AR government shock, ρ_g	[0,1)	Beta [0.5,0.2]	0.985	[0.981,0.989]
Belief shock volatility, σ_b	R^+	IGam [0.1,Inf]	0.630	[0.600,0.650]
SE technology shock, σ_x	R^+	IGam [0.1,Inf]	0.670	[0.630,0.720]
SE investment shock, σ_a	R^+	IGam [0.1,Inf]	0.560	[0.520,0.600]
SE preference shock, σ_Δ	R^+	IGam [0.1,Inf]	0.370	[0.350,0.390]
SE government shock, σ_g	R^+	IGam [0.1,Inf]	0.940	[0.890,0.980]
SE measurement error, σ_y^{me}	[0,0.29]	Uniform	0.290	[0.290,0.290]
Technology shock effect, Ω_x	[-3,3]	Uniform	-0.552	[-0.633,-0.475]
Investment shock effect, Ω_a	[-3,3]	Uniform	0.296	[0.199,0.394]
Preference shock effect, Ω_Δ	[-3,3]	Uniform	0.850	[0.723,0.975]
Government shock effect, Ω_g	[-3,3]	Uniform	0.234	[0.183,0.285]

Note: Standard deviations in percentages. Posterior distribution obtained using M-H algorithm, 1 million draws from two chains; first half of each chain discarded. Acceptance rate 25-30 percent.

The last two columns of Table 2 present the posterior means of the estimated parameters, along with their 90 percent posterior probability intervals. The parameters are precisely estimated as is evidenced by the percentiles. The estimated steady state of marginal cost implies a steady state markup of twenty percent. Preference and government spending shocks exhibit a high degree of persistence. The autocorrelation of the non-stationary technology shock is low but it is not inconsistent with the moderate values commonly found in the literature.

Table 3: Business cycle dynamics

	USA			Model		
x	σ_x	$\rho(x, \ln(Y_t/Y_{t-1})$	ACF	σ_x	$\rho(x, \ln(Y_t/Y_{t-1})$	ACF
$\ln(Y_t/Y_{t-1})$	0.88	1	0.32	0.96	1	0.29
$\ln(C_t/C_{t-1})$	0.53	0.55	0.32	0.70	0.74	0.11
$\ln(I_t/I_{t-1})$	2.21	0.70	0.59	3.09	0.89	0.36
$\ln(G_t/G_{t-1})$	1.08	0.26	0.14	0.94	0.23	0.00
$\ln(A_t/A_{t-1})$	0.60	-0.20	0.53	0.56	-0.12	0.04
$\ln(N_t/\bar{N})$	4.88	0.10	0.98	8.00	0.16	0.99

Table 3 reports the second moments calculated using U.S. data and compares these moments to those obtained from model simulations at the posterior mean. Overall, the estimated model matches the relative volatilities, the autocorrelations and cross-correlations with output. Table 4 displays the contribution of each structural shock which we list in the first column to the variances of key macroeconomic variables. The decomposition suggests that animal spirits shocks ε_t^b are the most important source of U.S. aggregate fluctuations. These shocks account for roughly a half of output growth. The Appendix presents a more detailed analysis of the beliefs driven cycle in the spirit of Burns and Mitchell (1946). The other aggregate demand shocks play a lesser role and the contribution of the two technology shocks is small at no more than twenty percent. For investment, the vast majority of its variations comes from animal spirits suggesting that much of the spending is driven by entrepreneurial sentiments.

Table 4: Unconditional variance decomposition

	$\ln(Y_t/Y_{t-1})$	$\ln(C_t/C_{t-1})$	$\ln(I_t/I_{t-1})$	$\ln(N_t/\bar{N})$	$\ln(G_t/G_{t-1})$	$\ln(A_t/A_{t-1})$
ε_t^b	52.33	8.94	71.80	26.86	0.00	0.00
ε_t^x	11.53	41.07	2.41	3.44	0.76	0.00
ε_t^a	6.33	3.01	7.14	10.18	0.13	100.00
ε_t^Δ	17.94	44.09	9.96	32.02	0.00	0.00
ε_t^g	11.87	2.88	8.69	27.51	99.11	0.00

Note: Variables listed in first column are belief, technology, investment-specific, preference and government shocks.

We identify the shocks by estimating in a system and it is thus fair to ask if the shocks are meaningfully labelled. More concretely, do the shocks share resemblance with empirical series that are computed with orthogonal information sets? To begin with, the estimated model's total factor productivity series is compared with Fernald's (2014) total factor productivity series for the United States.[4] Fernald's series are widely considered as the gold standard for this variable for which he adjusts for variations in factor utilization (labor effort and the workweek of capital) as well as labor skills. The results are reassuring as shown in Figure 3, for which both series were detrended to consider movements at business cycle frequencies only. Both productivity series not only have similar amplitudes, but their contemporaneous correlation comes in at 0.66. Next, Figure 4 compares the index of estimated confidence and the U.S. Business Confidence index. The estimated index was constructed by morphing the sunspots shocks into an index – by first-differencing – and then both indeces were band-pass filtered to concentrate on the relevant cycles. The two confidence series are correlated with coefficient 0.68. Clearly, the empirical confidence index is influenced by a raft of fundamental and non-fundamental shocks and we do not pretend the empirical data to exactly map our theoretical notion of animal spirits. We interpret, however, the relationship in Figure 3 as endorsing our estimation and support the case that estimated shocks reflect variations in people's expectations about the future path of the economy. Furthermore, our estimated disturbances share similarity to Angeletos, Collard and Dellas' (2016, Figure 8) confidence shocks. They argue in a class of unique-equilibrium models, however, the general idea of impulses as expectational shocks parallels our account, thus, we interpret the results as complementary stories of the business cycle.

[4] Growth of total factor productivity in our model is given by $(1-\alpha)(\hat{\mu}_t^x + \ln \mu^x)$.

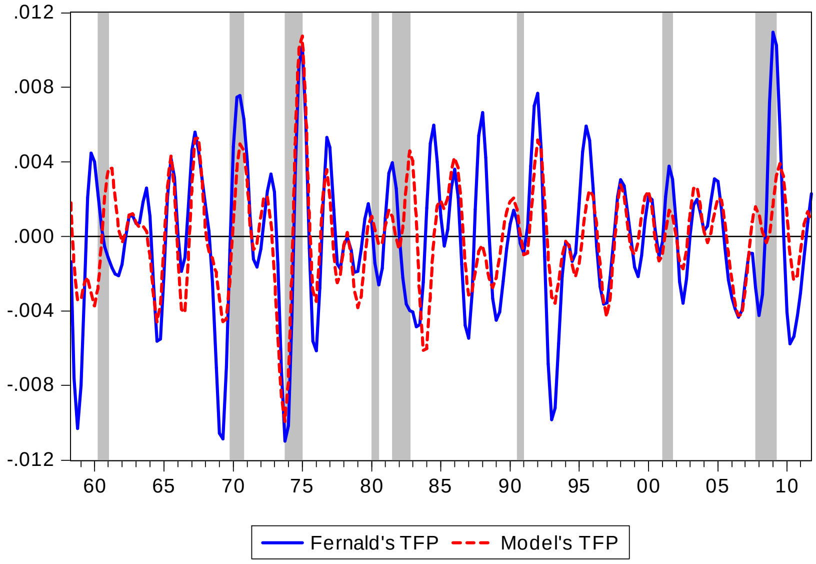

Figure 3: Fernald's vs Model's total factor productivity

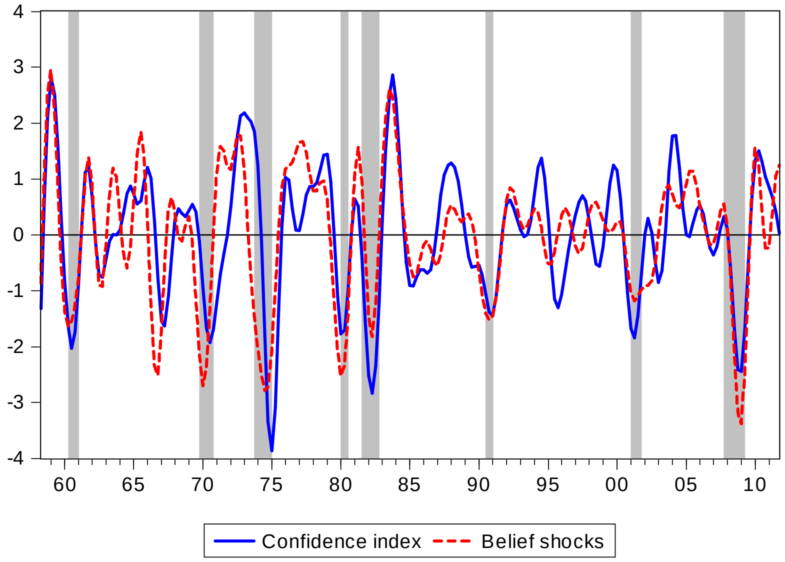

Figure 4: Business confidence index vs Belief shocks

4 Model extensions

Since the model features financial frictions, an objection to the validity of our story could be that the estimation has not included financial market information and why the artificial economy misses financial markets shocks. To ease these concerns, financial frictions will now come in two parts. In addition to the endogenous component which stands in for the feedback of the state of the economy on the financial sector, we now also allow exogenous disturbances that originate in the financial sector.

We denote these two parts by ξ_t as before and θ_t stands for stochastic disturbances as in Jermann and Quadrini (2012) and Liu, Wang and Zha (2013). The collateral shock θ_t evolves as

$$\ln \theta_t = (1-\rho_\theta)\ln \theta + \rho_\theta \ln \theta_{t-1} + \varepsilon_{\theta,t} \qquad 0 < \rho_\theta < 1$$

with $\varepsilon_{\theta,t} \backsim N(0, \sigma_\theta^2)$ and steady state value $\theta = 1$. The firms' borrowing constraint changes to

$$W_t(i)N_t(i) + r_t \kappa_t(i) \leq \theta_t \xi_t P_t(i) Y_t(i).$$

We re-estimate the model by additionally using financial data. The product $\theta_t \xi_t$ denotes financial tightness in the artificial economy and the additional observable variable in the measurement equation should share this characteristic. We decided to instrument financial market conditions by a credit spread similar to Christiano, Motto and Rostagno (2014). In particular, Christiano, Motto and Rostagno (2014) make use of the difference between the interest rate on Baa corporate bonds and the ten-year US government bond rate.[5] The corresponding measurement equation involves the demeaned (inverse) spread data $= x * \phi * \hat{\phi}_t$, where x is the scale parameter only appearing in the measurement equation to adjust the difference of the volatilities, that is units, between the model frictions and the observable variable. The values of calibrated parameters are set the same as before and we additionally estimate the financial shock's process and the scale parameter x. We set the prior mean for x to match the standard deviation of the smoothed financial frictions in the baseline model and the standard deviation of the demeaned spread data. We adopt an inverse gamma distribution for the prior. The model is estimated based on the previously used six observables plus the credit spread.

The posterior column of Table 5 reveals that adding financial information to

[5] We also estimate the model using loan data and animal spirits remain important.

Table 5: Estimation

Estimated parameters	Prior distribution		Posterior distribution	
	Range	Density [mean,std]	Mean	90% Interval
Steady-state marginal cost, ϕ	[0.83,0.90]	Beta [0.88,0.01]	0.832	[0.831,0.832]
Elasticity of collateral, ω	[1.984,7.566]	Uniform	4.488	[4.430,4.544]
Gov. trend smoothness, ψ_{yg}	[0,1)	Beta [0.5,0.2]	0.958	[0.948,0.968]
Scale parameter, x	R^+	IGam [44,Inf]	75.21	[72.37,77.97]
AR technology shock, ρ_x	[0,1)	Beta [0.5,0.2]	0.011	[0.003,0.018]
AR investment shock, ρ_a	[0,1)	Beta [0.5,0.2]	0.020	[0.010,0.029]
AR preference shock, ρ_Δ	[0,1)	Beta [0.5,0.2]	0.963	[0.956,0.970]
AR government shock, ρ_g	[0,1)	Beta [0.5,0.2]	0.982	[0.978,0.986]
AR financial shock, ρ_θ	[0,1)	Beta [0.5,0.2]	0.982	[0.980,0.983]
Belief shock volatility, σ_b	R^+	IGam [0.1,Inf]	0.730	[0.710,0.750]
SE technology shock, σ_x	R^+	IGam [0.1,Inf]	0.810	[0.750,0.870]
SE investment shock, σ_a	R^+	IGam [0.1,Inf]	0.550	[0.520,0.590]
SE preference shock, σ_Δ	R^+	IGam [0.1,Inf]	0.560	[0.540,0.590]
SE Government shock, σ_g	R^+	IGam [0.1,Inf]	0.940	[0.890,0.990]
SE financial shock, σ_θ	R^+	IGam [0.1,Inf]	0.220	[0.210,0.220]
SE measurement error, σ_y^{me}	[0,0.29]	Uniform	0.290	[0.290,0.290]
Technology shock effect, Ω_x	[-3,3]	Uniform	-0.482	[-0.543,-0.424]
Investment shock effect, Ω_a	[-3,3]	Uniform	0.240	[0.155,0.326]
Preference shock effect, Ω_Δ	[-3,3]	Uniform	0.647	[0.568,0.725]
Government shock effect, Ω_g	[-3,3]	Uniform	0.263	[0.215,0.308]
Financial shock effect, Ω_θ	[-3,3]	Uniform	0.967	[0.812,1.117]

the baseline setup does not change the estimates in any substantial manner. The 90 percent intervals are tight. The variance decomposition of the extended model is reported in Table 6. Most importantly, the credit spread (i.e. the financial frictions) is mainly driven by stochastic financial factors – by about sixty percent. As before, animal spirits remain the most critical driver of output fluctuations and they continue to account for forty percent of output growth variations. Financial shocks are considerably less relevant and explain about 18 percent.[6]

[6] In the Appendix, we run an estimation in which the financial shocks θ_t are correlated with the arsenal fundamental shocks. Animal spirits remain the main driver of the U.S. business cycle.

Table 6: Unconditional variance decomposition

	$\ln(Y_t/Y_{t-1})$	$\ln(C_t/C_{t-1})$	$\ln(I_t/I_{t-1})$	$\ln(N_t/\bar{N})$	Spread	$\ln(G_t/G_{t-1})$	$\ln(A_t/A_{t-1})$
ε_t^b	39.89	2.45	54.64	14.55	7.61	0.00	0.00
ε_t^x	12.51	38.28	2.44	2.16	1.38	1.56	0.00
ε_t^a	5.19	1.75	5.78	7.41	3.38	0.19	100.00
ε_t^Δ	17.29	43.72	12.29	27.00	15.63	0.00	0.00
ε_t^g	6.97	0.63	4.28	12.44	7.79	98.25	0.00
ε_t^θ	18.16	13.17	20.57	36.45	64.21	0.00	0.00

Figure 5 visualizes the effects of moving to the extended model and to the new estimation. The figure plots the estimated old and new smoothed financial frictions vis-a-vis the smoothed financial shocks. Foremost, without financial market data and financial shocks, the estimated financial frictions (blue dash line) are more volatile. When including financial market data and shocks, financial frictions (red solid line, matched to scaled negative spread data) are highly correlated with the financial shock (green line). Before all else, this is the case during the depth of the Great Recession. Essentially the added financial shocks eat up a large fraction of the animal spirits shocks, but only during the Great Recession period. This pattern can be seen in Figure 6 which plots the old and new series of confidence. They are almost identical except for the 2007-2009 period.

As before, we close the discussion by posing the following question: if estimated financial frictions have resemblance to empirical measures i.e. do financial friction shocks and financial conditions indicators look alike? Figure 7 plots the theoretical notion side by side with the U.S. National Financial Condition Index for the period around the Great Recession (the index is not available for our complete sample period and we restrict the graph to illustrate the main point). In the figure, negative values of the index indicate financial conditions that are tighter than average, while positive values indicate financial conditions are looser than average. The index points to a worsening of financial conditions in the U.S. starting in the middle of 2007. The estimated financial frictions show substantial conformity with the index. Both series begin to fall at about the same time and also reach their lower turning point in the last quarter of 2008.

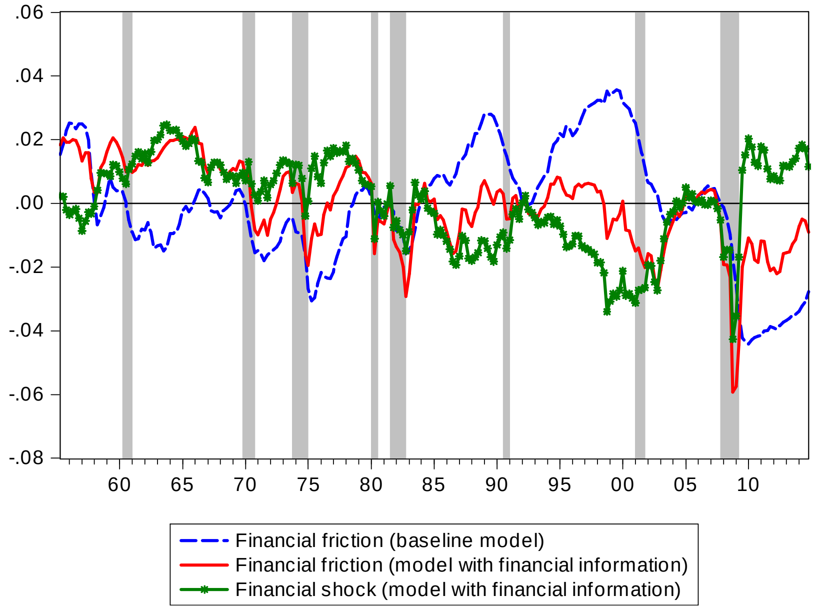

Figure 5: Estimated financial friction and financial shock. The blue dash line represents the estimated smoothed financial friction in baseline model. The red and green lines represent the financial friction and the financial shock in extended setup.

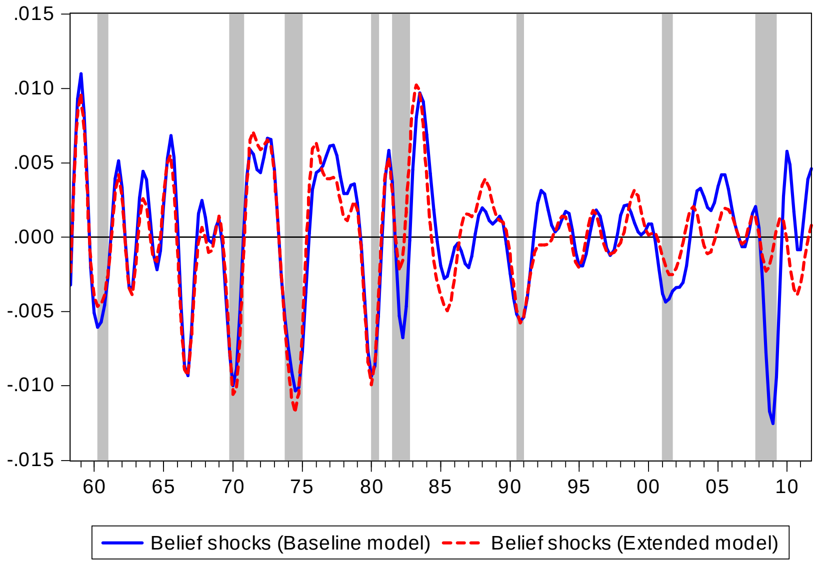

Figure 6: Two series of animal spirits

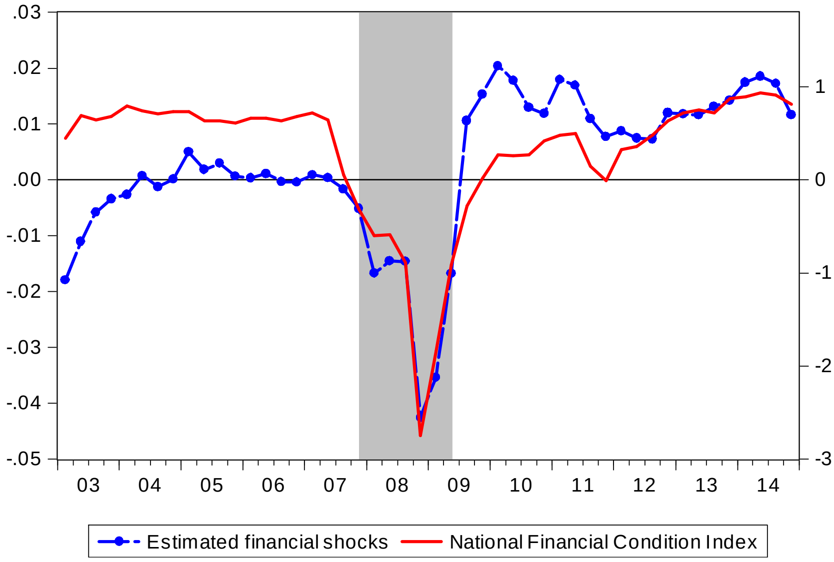

Figure 7: Shocks and Financial Condition Index (on right-hand scale)

5 Checks of robustness

In order to evaluate the sensitivity of our findings, we conduct two robustness checks using the extended model of section 4. In particular, we provide evidence regarding the choices of the expectation error. We also employ further, alternative observables to measure the conditions prevailing in the financial markets as well as total factor productivity.

5.1 Alternative expectations errors

We have so far attached the forecast error to output during the estimation. Next we re-estimate two alternatives. Model 2 delegates the expectation error alternatively to consumption, i.e. to η_t^c. As before, the error is separated into fundamental and non-fundamental components. In Model 3, we follow the approach discussed in Farmer, Kharamov and Nicolò (2015): the forecast error of output η_t^y is simply the belief shock with variance σ_η^2. However, the expectation error is correlated with the fundamental shocks. Thus we estimate these correlations, the priors of which are uniformly distributed indicating that we are agnostic about the relation. Table 7 shows that the posterior distributions of the parameter estimates

Table 7: Posterior distribution comparison

	Model 1: η_t^y		Model 2: η_t^c		Model 3: $\eta_t^y = \varepsilon_t^b$	
Parameter	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
ϕ	0.832	[0.831,0.832]	0.832	[0.831,0.832]	0.832	[0.831,0.832]
ω	4.488	[4.430,4.544]	4.487	[4.430,4.544]	4.487	[4.428,4.543]
ψ_{yg}	0.958	[0.948,0.968]	0.958	[0.948,0.968]	0.958	[0.948,0.968]
x	75.21	[72.37,77.97]	75.18	[72.43,78.02]	75.20	[72.45,78.06]
ρ_x	0.011	[0.003,0.018]	0.011	[0.003,0.018]	0.011	[0.003,0.018]
ρ_a	0.020	[0.010,0.029]	0.020	[0.010,0.030]	0.020	[0.010,0.029]
ρ_Δ	0.963	[0.956,0.970]	0.963	[0.956,0.970]	0.963	[0.956,0.970]
ρ_g	0.982	[0.978,0.986]	0.982	[0.978,0.986]	0.982	[0.978,0.986]
ρ_θ	0.982	[0.980,0.983]	0.982	[0.980,0.983]	0.982	[0.980,0.983]
σ_b	0.730	[0.710,0.750]	0.120	[0.120,0.130]	–	–
σ_η	–	–	–	–	0.970	[0.930,1.000]
σ_x	0.810	[0.750,0.870]	0.810	[0.740,0.870]	0.800	[0.750,0.870]
σ_a	0.550	[0.520,0.590]	0.550	[0.510,0.580]	0.550	[0.520,0.580]
σ_Δ	0.560	[0.540,0.590]	0.560	[0.540,0.590]	0.560	[0.540,0.590]
σ_g	0.940	[0.890,0.990]	0.940	[0.890,0.990]	0.940	[0.890,0.990]
σ_θ	0.220	[0.210,0.220]	0.220	[0.210,0.220]	0.220	[0.210,0.220]
σ_y^{me}	0.290	[0.290,0.290]	0.290	[0.290,0.290]	0.290	[0.290,0.290]
Ω_x	-0.482	[-0.543,-0.424]	-0.265	[-0.275,-0.255]	–	–
Ω_a	0.240	[0.155,0.326]	0.317	[0.302,0.331]	–	–
Ω_Δ	0.647	[0.568,0.725]	1.109	[1.096,1.122]	–	–
Ω_g	0.263	[0.215,0.308]	0.044	[0.037,0.052]	–	–
Ω_θ	0.967	[0.812,1.117]	1.479	[1.453,1.504]		
$\rho(x,\eta^y)$	–	–	–	–	-0.398	[-0.450,-0.348]
$\rho(a,\eta^y)$	–	–	–	–	0.135	[0.085,0.184]
$\rho(\Delta,\eta^y)$	–	–	–	–	0.374	[0.333,0.415]
$\rho(g,\eta^y)$	–	–	–	–	0.253	[0.210,0.295]
$\rho(\theta,\eta^y)$	–	–	–	–	0.215	[0.181,0.248]
Log data density	3442.527		3436.977		3444.077	

remain almost identical. Furthermore, the log data densities for all three models are essentially the same.

5.2 Alternative observable variables

The second robustness check concerns the choice of the observed spread when instrumenting financial markets conditions. We thus consider the sensitivity to using various alternative spreads. In particular, we sequentially explore if (i) the Baa-Aaa spread, (ii) the Baa-Federal funds rate spread or (iii) the Gilchrist and Zakrajšek' (2012) spread yield significantly different results in the estimation. We report the variance decompositions only. The results for the Baa-Aaa and Baa-

Federal funds rate spreads are reported in Tables 8 and 9. Animal spirits continue to stand out as the main driver of the business cycle. The Tables suggest that they account for about 40 percent of the U.S. output fluctuations. Only when using Gilchrist and Zakrajšek's (2012) spread do financial shocks' contributions climb to over twenty percent. However, this change appears to be mainly the outcome of a shorter sample given the spread's availability from the mid-1970s onwards. Consequentially, a stronger weight is put onto the Great Recession period. To confirm this, we re-estimated the model using the other spreads, but only covering the 1973 to 2014 period. As expected, the results then came out very similar to Table 10's.

Table 8: Unconditional variance decomposition (Baa-Aaa spread)

	$\ln(Y_t/Y_{t-1})$	$\ln(C_t/C_{t-1})$	$\ln(I_t/I_{t-1})$	$\ln(N_t/\bar{N})$	Spread	$\ln(G_t/G_{t-1})$	$\ln(A_t/A_{t-1})$
ε_t^b	41.92	2.71	57.53	16.37	8.55	0.00	0.00
ε_t^x	13.15	39.03	2.58	2.00	1.27	1.80	0.00
ε_t^a	4.98	1.75	5.53	7.53	3.43	0.21	100.00
ε_t^Δ	16.97	43.16	11.68	26.66	15.27	0.00	0.00
ε_t^g	6.42	0.59	3.71	11.44	7.16	97.99	0.00
ε_t^θ	16.57	12.75	18.96	36.00	64.32	0.00	0.00

Table 9: Unconditional variance decomposition (Baa-FF spread)

	$\ln(Y_t/Y_{t-1})$	$\ln(C_t/C_{t-1})$	$\ln(I_t/I_{t-1})$	$\ln(N_t/\bar{N})$	Spread	$\ln(G_t/G_{t-1})$	$\ln(A_t/A_{t-1})$
ε_t^b	42.09	2.78	58.23	16.58	9.00	0.00	0.00
ε_t^x	12.75	42.22	2.48	2.03	1.33	1.59	0.00
ε_t^a	5.94	2.26	6.61	9.12	4.29	0.22	100.00
ε_t^Δ	15.78	39.22	9.60	23.94	14.66	0.00	0.00
ε_t^g	6.87	0.66	4.13	12.84	8.34	98.19	0.00
ε_t^θ	16.56	12.86	18.95	35.49	62.38	0.00	0.00

Table 10: Unconditional variance decomposition (Gilchrist and Zakrajšek' spread)

	$\ln(Y_t/Y_{t-1})$	$\ln(C_t/C_{t-1})$	$\ln(I_t/I_{t-1})$	$\ln(N_t/\bar{N})$	*Spread*	$\ln(G_t/G_{t-1})$	$\ln(A_t/A_{t-1})$
ε_t^b	27.75	1.32	40.06	14.55	4.18	0.00	0.00
ε_t^x	12.19	32.73	2.44	2.59	0.94	1.25	0.00
ε_t^a	6.79	1.87	5.78	7.79	2.91	0.17	100.00
ε_t^Δ	22.77	43.72	16.62	27.00	16.40	0.00	0.00
ε_t^g	8.49	0.53	4.81	12.44	4.66	98.58	0.00
ε_t^θ	22.00	13.82	28.14	36.45	70.91	0.00	0.00

Unlike in the above estimations, we also added total factor productivity to the catalog of observables. Fernald's (2014) continuously updated data is the natural series to choose. Fernald adjusts for variations in factor utilization (labor and capital) and includes adjustment for quality or composition. Most of these influences are not part of the artificial economy and we thus add one more measurement error on total factor productivity (at not more than ten percent). Table 11 shows that our results remain robust. Animal spirits continue to cause the bulk of U.S. output fluctuations. The two technology shocks' contributions are lower, with a best point estimate near 20 percent.

Table 11: Unconditional variance decomposition (Fernald TFP)

	$\ln(\frac{Y_t}{Y_{t-1}})$	$\ln(\frac{C_t}{C_{t-1}})$	$\ln(\frac{I_t}{I_{t-1}})$	$\ln(\frac{N_t}{\bar{N}})$	Spread	$\ln(\frac{G_t}{G_{t-1}})$	$\ln(\frac{A_t}{A_{t-1}})$	$\ln(\frac{TFP_t}{TFP_{t-1}})$
ε_t^b	40.26	2.31	56.12	15.44	8.35	0.00	0.00	0.00
ε_t^x	15.44	45.60	2.98	2.63	1.74	1.91	0.00	100.00
ε_t^a	5.04	1.62	5.73	7.55	3.56	0.18	100.00	0.00
ε_t^Δ	15.73	38.66	11.43	26.44	15.90	0.00	0.00	0.00
ε_t^g	6.99	0.59	4.29	12.80	8.27	97.91	0.00	0.00
ε_t^θ	16.54	11.22	19.44	35.14	62.18	0.00	0.00	0.00

6 A closer look at the Great Recession

From 2007 to 2009 the U.S. economy was tightly gripped in the turmoils of a severe recession. The Great Recession was the worst economic contraction since the 1930s, with economic activity diving after various financial institutions collapsed. While our discussion has suggested that financial shocks have only played a small role for U.S. fluctuations, the Great Recession is arguably closely linked to financial factors. Can such a statement be reconciled with our earlier findings? To provide an answer, we plot the historical decomposition of the structural shocks to output growth for the 2007:III to 2011:IV period. This is done for the benchmark model as well as the extended model which includes the stochastic financial frictions. Figure 8a reports the baseline model without exogenous financial frictions and it suggests that the Great Recession was caused by a sudden pessimism. Figure 8b hints at a different storyline. Here, financial disturbances drag down the economy from the end of 2007 onwards and the data favors the interpretation that the Great Recession was closely associated with the financial factors with the sharp contraction of output after 2007 almost exclusively being caused by financial shocks.

What is our take on these results? We believe it boils down to pinning down the economics behind the idea of financial shocks θ_t. As we have seen by adding financial shocks to the model, the main effect on the estimation part was to absorb a fraction of the original baseline model's animal spirits and in particular, this was mainly the case for the Great Recession period (recall Figure 6). We have two possible interpretations. The first reading is that financial frictions indeed are exogenous and they reflect changes that we have not modelled such like changes to bank's credit policies, or the rise and fall of U.S. real estate prices and their effect on financial markets. However, there is an alternative interpretation: financial friction shocks are merely representing the transmission of other shocks and perhaps are animal spirits in disguise.[7] At times changes to credit conditions arise exogenously but often they echo changes in the economy. When after 2006 housing prices fell, when banks curbed lending and tightened credit, when investors stopped borrowing, then this happened because people were expecting worsening conditions and higher defaults. Phrased alternatively, people became pessimistic and, as a consequence of the effect on financial markets, this pessimism became self-fulfilling. We believe that both interpretation do not rule out each other and are complementary, thus, we leave open as which interpretation we favor.

[7] We would like to thank Jess Benhabib for suggesting this interpretation to us.

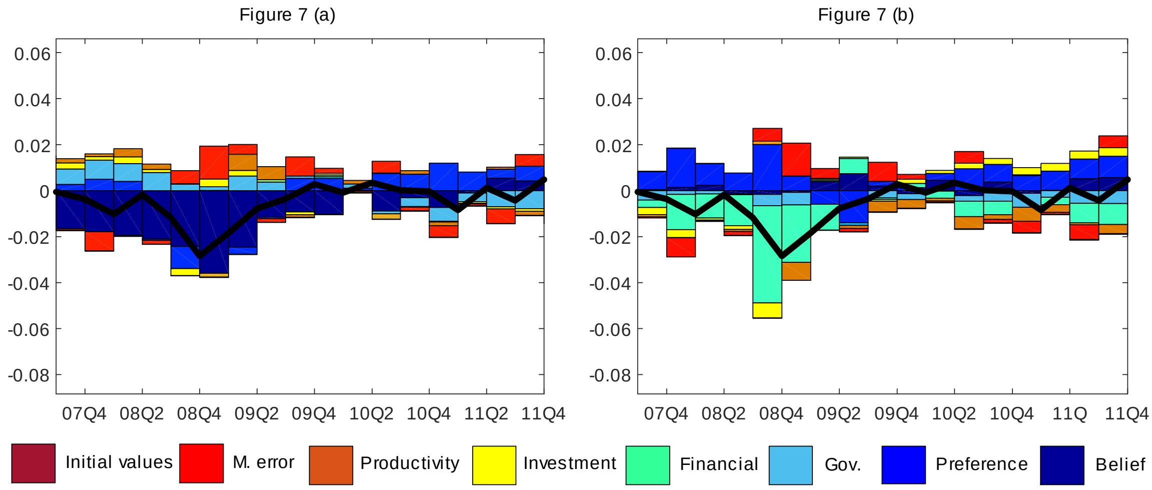

Figure 8: Historical decomposition of output growth

7 Concluding remarks

This paper has presented evidence on the sources of U.S. aggregate fluctuations over the period 1955 to 2014. We perform a Bayesian estimation of a financial accelerator model which features an indeterminacy of rational expectations equilibria. We allow for the possibility that business cycles can be driven both by fundamental shocks as well as by animal spirits. Our results support the view that people's animal spirits have played a significant role for the U.S. business cycle. Variance decompositions suggest that animal spirits are behind around forty percent of output growth variations. Technology shocks and financial frictions shocks are significantly less important and they both explain not more than 20 percent of output variations. One recession stands out. The 2007-2009 recession appears to have been chiefly caused by a tightening of the economy's financing conditions. However, our analysis is not able to give a definite interpretation to what has caused this tightening.

References

[1] Adelman, F., and Adelman, I. (1959): "The dynamic properties of the Klein-Goldberger model", Econometrica 27, 596-625.

[2] Angeletos, G.M., Collard, F. and Dellas, H. (2016): "Quantifying confidence", University of Bern, mimeo.

[3] Baxter, M. and King, R.G. (1991): "Productive externalities and business cycles", Federal Reserve Bank of Minneapolis, mimeo.

[4] Benhabib, J. and Wang, P. (2013): "Financial constraints, endogenous markups, and self-fulfilling equilibria", Journal of Monetary Economics 60, 789-805.

[5] Bernanke, B.S., Gertler, M. and Gilchrist, S. (1999): "The financial accelerator in a quantitative business cycle framework", in: Handbook of Macroeconomics, Taylor J.B. and M. Woodford (editors), 1341-1393, Elsevier.

[6] Burns, A.F. and Mitchell, W.C. (1946): "Measuring business cycles", NBER, New York.

[7] Christiano, L.J., Motto, R. and Rostagno, M. (2014): "Risk shocks", American Economic Review 104, 27-65.

[8] Christiano, L.J., Trabandt, M. and Walentin, K. (2011): "Introducing financial frictions and unemployment into a small open economy model", Journal of Economic Dynamics and Control 35, 1999-2041.

[9] Clarke, C. (2009): "An Interview with Kenneth Arrow", The Atlantic July 27, 2009.

[10] Cogley, T. and Sbordone, A.M. (2008): "Trend inflation, indexation, and inflation persistence in the New Keynesian Phillips curve", American Economic Review 98, 2101-2126.

[11] Del Negro, M., M. Giannoni and F. Schorfheide (2015): "Inflation in the Great Recession and New Keynesian models", American Economic Journal: Macroeconomics 7, 168-196.h

[12] Dotsey, M. and King, R.G. (2005): "Implications of state-dependent pricing for dynamic macroeconomic models", Journal of Monetary Economics 52, 213-242.

[13] Farmer, R.E., Khramov, V. and Nicolò, G. (2015): "Solving and estimating indeterminate DSGE models", Journal of Economic Dynamics and Control 54, 17-36.

[14] Fernald, J. (2014): "A quarterly, utilization-adjusted series on total factor productivity", Federal Reserve Bank of San Francisco, mimeo.

[15] Gilchrist, S. and Zakrajšek, E. (2012): "Credit spreads and business cycle fluctuations", American Economic Review 102, 1692-1720.

[16] Jermann, U. and Quadrini, V. (2012): "Macroeconomic effects of financial shocks", The American Economic Review 102, 238-271.

[17] Justiniano, A., Primiceri, G.E. and Tambalotti, A. (2011): "Investment shocks and the relative price of investment", Review of Economic Dynamics 14, 102-121.

[18] King, R.G. and Plosser, C.I. (1994): "Real business cycles and the test of the Adelmans", Journal of Monetary Economics, 33, 405-438.

[19] Kiyotaki, N. and Moore, J. (1997): "Credit cycles", Journal of Political Economy 105, 211-248.

[20] Liu, Z., Wang, P. and Zha, T. (2013): "Land-price dynamics and macroeconomic fluctuations", Econometrica, 81, 1147-1184.

[21] Lubik, T.A. and Schorfheide, F. (2003): "Computing sunspot equilibria in linear rational expectations models", Journal of Economic Dynamics and Control 28, 273-285.

[22] Merton, R. (1948): "The self-fulfilling prophecy", The Antioch Review 8, 193-210.

[23] Nolan, C. and Thoenissen, C. (2009): "Financial shocks and the US business cycle", Journal of Monetary Economics, 56, 596-604.

[24] Otrok, C. (2001): "On measuring the welfare cost of business cycles," Journal of Monetary Economics 47, 61-92.

[25] Pavlov, O. and Weder, M. (2017): "Product scope and endogenous fluctuations", Review of Economic Dynamics, 24, 175-191.

[26] Pintus, P., Wen, Y. and Xing, X. (2015): "Interest rate dynamics, variable-rate loan contracts, and the business cycle", Federal Reserve Bank of St. Louis, mimeo.

[27] Schmitt-Grohé, S. and Uribe, M. (2012): "What's news in business cycles?", Econometrica 80, 2733-2764.

[28] Wang, P. and Z. Liu (2014): "Credit Constraints and self-fulfilling business cycles", American Economic Journal: Macroeconomic 6, 32-69.

[29] Weder, M. (2006): "The role of preference shocks and capital utilization in the Great Depression", International Economic Review 47, 1247-1268.

8 Appendix - not to be published

The Appendix sets out the complete model, a discussion of the typical animal spirits cycle, allow the case in which for financial and fundamental shocks to be correlated, and it gives the data sources and definitions.

8.1 Model equations and equilibrium dynamics

The first-order conditions for the household's optimization problems are

$$\varphi N_t^{\frac{1}{\eta}} = \frac{1}{C_t - \Delta_t} W_t$$

$$r_t = A_t \delta_0 u_t^{\nu}$$

and

$$\frac{A_t}{C_t - \Delta_t} = \beta E_t \left[\frac{1}{C_{t+1} - \Delta_{t+1}} (r_{t+1} u_{t+1} + A_{t+1}(1 - \delta_{t+1})) \right].$$

In the model, output, consumption, and real wage fluctuate around the same stochastic growth trend $X_t^Y = X_t A_t^{\alpha/(\alpha-1)}$, the growth rate of which is $\mu_t^y \equiv X_t^Y / X_{t-1}^Y = \mu_t^x (\mu_t^a)^{\frac{\alpha}{\alpha-1}}$. The trend in capital stock, which is also the trend in investment equals $X_t^K = X_t^Y / A_t$, the growth rate of which is $\mu_t^k \equiv X_t^K / X_{t-1}^K = \mu_t^x (\mu_t^a)^{\frac{1}{\alpha-1}}$. Besides, the government expenditure fluctuates around its own trend X_t^G. There is no growth trend in hours, utilization and marginal cost. We first derive the detrended dynamic equilibrium equations and then log-linearly approximate them around the deterministic steady state. Let $y_t = Y_t / X_t^Y$, $c_t = C_t / X_t^Y$, $w_t = W_t / X_t^Y$, $i_t = I_t / X_t^K$, $k_t = K_t / X_{t-1}^K$, $g_t = G_t / X_t^G$, and $y_t / \bar{y}$ approximately equal to $Y_t / \bar{Y}_t$, where $\bar{y}$ represents the steady state of detrended output. The log-linearized system is summarized by

$$\hat{y}_t = \alpha \hat{k}_t + \alpha \hat{u}_t - \alpha \hat{\mu}_t^k + (1 - \alpha) \hat{N}_t$$

$$\hat{y}_t = [1 - \frac{\alpha \phi (\mu^k - 1 + \delta)}{\delta (1 + \nu)} - \frac{\bar{G}}{\bar{Y}}] \hat{c}_t + \frac{\alpha \phi (\mu^k - 1 + \delta)}{\delta (1 + \nu)} \hat{\imath}_t + \frac{\bar{G}}{\bar{Y}} (\hat{a}_t^g + \hat{g}_t)$$

$$\hat{y}_t = (1+\eta^{-1})\hat{N}_t + \hat{c}_t - \hat{\Delta}_t - \hat{\phi}_t$$

$$\hat{y}_t = (1+\nu)\hat{u}_t + \hat{k}_t - \hat{\phi}_t - \hat{\mu}_t^k$$

$$\hat{k}_{t+1} = \frac{(1-\delta)}{\mu^k}(\hat{k}_t - \hat{\mu}_t^k) + \frac{(\mu^k - 1 + \delta)}{\mu^k}\hat{\imath}_t - \frac{\delta(1+\nu)}{\mu^k}\hat{u}_t$$

$$\hat{c}_{t+1} = \hat{c}_t - \hat{\Delta}_t - [1 - \frac{\beta\delta(1+\nu)}{\mu^k}]\hat{\mu}_{t+1}^k + \hat{\Delta}_{t+1} + \frac{\beta\delta(1+\nu)}{\mu^k}(\hat{y}_{t+1} - \hat{k}_{t+1} + \hat{\phi}_{t+1} - \hat{u}_{t+1})$$

and

$$\hat{\phi}_t = \frac{1}{\phi\omega}\hat{y}_t + \hat{\theta}_t.$$

In these equations, variables without time subscripts refer to steady state values while the hatted variables denote percent deviations from their corresponding steady-state, e.g., $\hat{y}_t \equiv \log(y_t/\bar{y})$.

8.2 A Burns-Mitchell analysis of animal spirits

We employ a classical method of business cycle analysis developed by Burns and Mitchell (1946) and Adelman and Adelman (1959) to evaluate the belief shock driven model in terms of whether it mimics the cyclical behavior of post war U.S. data.[8] A brief description of the idea follows. The business cycle series consist of a sequence of reference cycles, measured trough-to-trough by convention. We use NBER dates to determine the peak of the reference cycle for both U.S. and artificially generated data. Our sample series includes eight complete trough-peak-trough cycles beginning in 1958:II and ending with the lower turning point in 2009:II. No prior filtering or detrending of the data has been undertaken that is we do not detrend the model output to allow for the presence of long-run technological progress and bring it in line with empirical data. Each complete reference cycle is divided into nine stages (I to IX). Stage I is the initial trough; stage V is the reference peak, and stage IX is the terminal trough. The expansion phase (stages I to V) is divided into three substages (II, III, and IV) of equal length (excluding time contained in stages I and V). The contraction phase (stages V

[8]King and Plosser (1994) for a concise summary of the Burns-Mitchell procedure as well as its implementation in a general equilibrium context.

to IX) is measured in an analogous fashion. Next, each observation in the cycle is expressed as a percentage of the cycle mean called cycle relatives. Mean cycle relatives per stage are averaged across all reference cycles to yield a graphical summary of an average business cycle in the nine-point-plot of Figure 8. The plot provides a visual impression of both the simulated data and the U.S. data.

Concretely, Figure 9 displays the average behavior, in cycle relatives, over the nine stages of the business cycle for per capita real GDP and the artificial equivalent when the model is counterfactually driven by belief shocks only. Stage I coincides with the initial trough, stage V with the peak, and stage IX corresponds to the terminal trough. The similar general shape of the two series demonstrates that artificial series matches well postwar U.S. cycles. The per capita real GDP exhibits a distinct pro-cyclical pattern, rising during expansions and falling during contractions. Both series peak in the same stage.

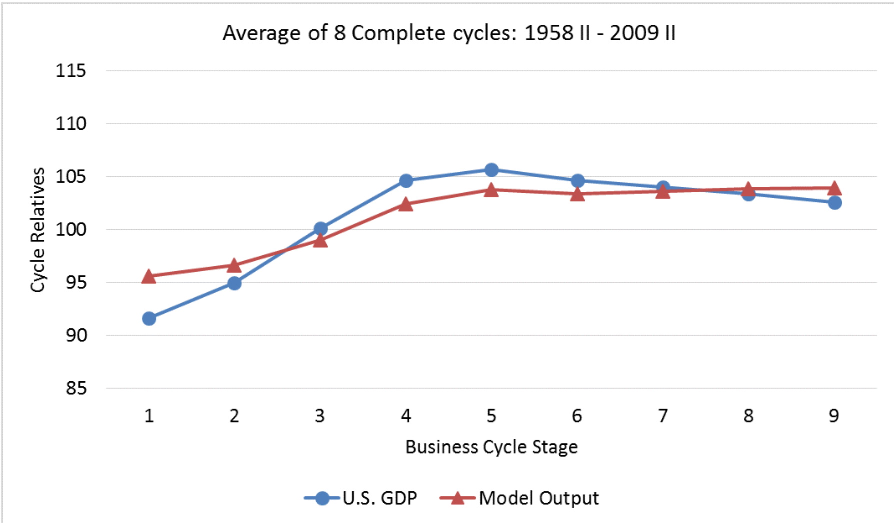

Figure 9: Nine-point graph for U.S. GDP and counterfactually belief driven output

8.3 Correlated financial shocks

In section 4, we assume that fundamental shocks are independent from each other. Since financial shocks are shocks to variables that might reflect people's expectations about future economic conditions, it is reasonable to investigate if such extension affects our results. We re-estimate the economy while allowing for non-zero correlations between financial and the other fundamental shocks. Table

12 indicates that animal spirits shocks remains the most important source of output fluctuations at close to one half and financial shocks explain somewhat less than 20 percent.

Table 12: Unconditional variance decomposition

	$\ln(Y_t/Y_{t-1})$	$\ln(C_t/C_{t-1})$	$\ln(I_t/I_{t-1})$	$\ln(N_t/\bar{N})$	Spread	$\ln(G_t/G_{t-1})$	$\ln(A_t/A_{t-1})$
ε_t^b	45.38	4.91	65.35	22.96	12.13	0.00	0.00
ε_t^x	15.45	41.91	3.37	1.91	1.89	1.04	0.00
ε_t^a	6.94	3.01	7.96	11.97	6.05	0.13	100.00
ε_t^Δ	9.55	31.14	2.06	10.20	12.45	0.00	0.00
ε_t^g	3.12	1.34	0.27	5.92	0.26	98.83	0.00
ε_t^θ	19.57	17.69	20.99	47.05	67.22	0.00	0.00

8.4 Data description

This appendix is to describe the details of the source and construction of the data used in estimation. The sample period covers the first quarter of 1955 through the fourth quarter of 2014:

1. Real Gross Domestic Product. Billions of Chained 2009 Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 1.1.6.

2. Gross Domestic Product. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

3. Personal Consumption Expenditures, Nondurable Goods. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

4. Personal Consumption Expenditures, Services. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

5. Gross Private Domestic Investment, Fixed Investment, Residential. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

6. Gross Private Domestic Investment, Fixed Investment, Nonresidential. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

7. Government Consumption Expenditure. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 3.9.5.

8. Government Gross Investment. Billions of Dollars, Seasonally Adjusted Annual Rate. Source: Bureau of Economic Analysis, NIPA Table 3.9.5.

9. Nonfarm Business Hours. Index 2009=100, Seasonally Adjusted. Source: Bureau of Labor Statistics, Series Id: PRS85006033.

10. Relative Price of Investment Goods. Index 2009=1, Seasonally Adjusted. Source: Federal Reserve Economic Data, Series Id: PIRIC.

11. Civilian Noninstitutional Population. 16 years and over, thousands. Source: Bureau of Labor Statistics, Series Id: LNU00000000Q.

12. Confidence: Business Tendency Survey for Manufacturing, Composite Indicators, OECD Indicator for the United States, Series Id: BSCICP03USM665S.

13. Total Factor Productivity. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity", retrieved from

http://www.frbsf.org/economicresearch/economists/john-fernald/.

14. Moody's Seasoned Baa Corporate Bond Yield, Not Seasonally Adjusted, Average of Daily Data, Percent. Source: Board of Governors of the Federal Reserve System.

15. Moody's Seasoned Aaa Corporate Bond Yield, Not Seasonally Adjusted, Average of Daily Data, Percent. Source: Board of Governors of the Federal Reserve System.

16. 10 Year Treasury Constant Maturity Rate, Not Seasonally Adjusted, Average of Daily Data, Percent. Source: Board of Governors of the Federal Reserve System.

17. Effective Federal Funds Rate, Not Seasonally Adjusted, Average of Daily Data, Percent. Source: Board of Governors of the Federal Reserve System.

18. Chicago Fed National Financial Conditions Index, Not Seasonally Adjusted. Source: Federal Reserve Bank of Chicago.

19. GDP deflator= (2)/(1).

20. Real Per Capita Output, $Y_t = (1)/(11)$.

21. Real Per Capita Consumption, $C_t = [(3) + (4)]/(19)/(11)$.

22. Real Per Capita Investment, $I_t = [(5) + (6)]/(19)/(11)$.

23. Real Per Capita Government Expenditure, $G_t = [(7) + (8)]/(19)/(11)$.

24. Per Capita Hours Worked, $N_t = (9)/(11)$.
25. Credit spread $= (14) - (16)$.