Animal Spirits, Financial Markets and Aggregate Instability*

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Abstract

People's animal spirits are prime drivers of U.S. business cycle fluctuations. This finding is demonstrated within an estimated artificial macroeconomy of financial market frictions. Animal spirits shocks account for well over a third of output fluctuations over the period from 1955 to 2014. Financial friction and technology shocks are considerably less important. We also find that a substantial part of aggregate output's contraction during the Great Recession was caused by adverse shocks to expectations.

* *Keywords:* Animal spirits, business cycles, Bayesian estimations, endogenous financial frictions, indeterminacy, DSGE. *JEL classification:* **E32**, **E44**.

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1 Introduction

What are the shocks that cause macroeconomies to experience recurrent sequences of booms and slumps? The current paper pursues this question by presenting evidence on the sources of business cycles for the post-Korean War American economy. The results support the view that people's psychological motivations, a.k.a. animal spirits, provoke a significant portion of the fluctuations in aggregate real economic activity, causing well over one third of U.S. output volatility. This finding is demonstrated within an artificial economy of financial market frictions. Our exercise also suggests that it was chiefly adverse shocks to expectations that led to the Great Recession.

Models with credit market frictions have become popular since the Great Recession, reflecting the notion that disruptions to financial markets were the key factors behind this contraction. Building on earlier work, such as Kiyotaki and Moore (1997) as well as Bernanke et al. (1999), this research has shown how financial market frictions can amplify shocks to macroeconomic fundamentals by transforming small economic disturbances into large business cycles.[1] Christiano et al. (2015), for example, extend New Keynesian models by financial market frictions to explain some key aspects of the Great Recession.

We depart from the aforementioned works twofold. First, the parametric space of our model includes multiple equilibria. This multiplicity will be cleared up by people's animal spirits that select from the possible equilibrium outcomes. Second, unlike most existing work on such indeterminacy, the analysis concentrates on estimating the artificial economy: we focus on the empirical implications of the multiplicity by explicitly analyzing the business cycle variance contributions of animal spirits or belief shocks. The undertaking is implemented by building on a variant of Benhabib and Wang (2013).[2] Indeterminacy in this model is linked to the empirically observed

[1] See also Liu et al. (2013) and Nolan and Thoenissen (2009).

[2] Azariadis et al. (2016), Liu and Wang (2014) and Harrison and Weder (2013) are other models

countercyclical movement of financial market tightness. Figure 1 plots the cyclical pattern of financial market health. It measures financial health by the Baa Corporate Bond spread which is displayed on an inverted scale and is plotted opposite the fluctuations of per capita GDP. The shaded areas in the figure correspond to NBER recessions. They highlight that financial conditions are not only cyclical, but also deteriorate markedly during most slumps.

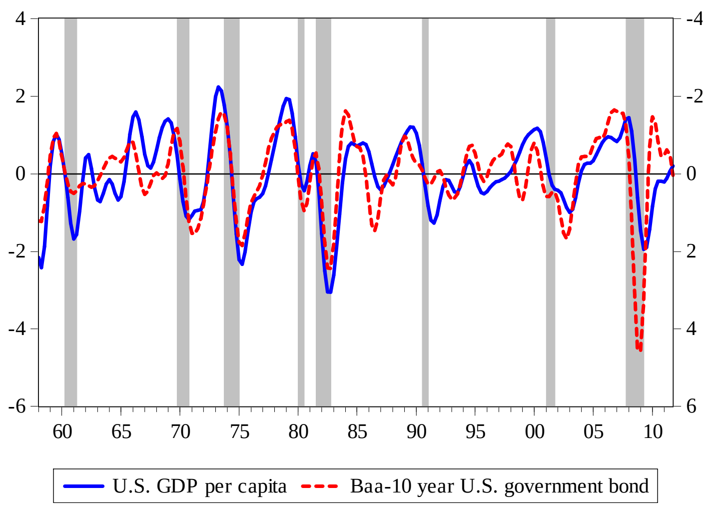

Figure 1: U.S. GDP and credit spread (on right-hand scale) at business cycle frequencies. Shaded areas indicate NBER recessions.

In the artificial economy, countercyclical financial health is a key mechanism to multiplicity. It is the endogenous interaction of a time varying (flow) collateral constraint and a countercyclical markup that spawns equilibrium indeterminacy, a condition that allows aggregate fluctuations to be caused by extrinsic changes in people's expectations. Moreover, in addition to such animal spirits shocks, the economy is buffeted by an array of fundamental shocks. The model is estimated by full information Bayesian methods using quarterly U.S. data covering the period from 1955:I to 2014:IV. This approach follows for example Justiniano et al. (2011) as well

of various stripes that combine multiple equilibria and financial frictions.

as Schmitt-Grohé and Uribe (2012), who, however, only explore the role of fundamental shocks as the engines of business cycles. The key result that ensues from the Bayesian estimation is that animal spirits are important drivers of the repeated fluctuations of the U.S. macroeconomy. Specifically, by computing forecast error variance decompositions, we find that animal spirits account for about 40 percent of U.S. output variations and for about two thirds of the fluctuations in investment. Disturbances that originate in the financial sector explain less than ten percent of output fluctuations. Moreover, we show that belief shocks have played an important role in the sharp contraction in economic activity of the Great Recession that began at the end of 2007.

Previous work on multiple equilibria in real economies has overwhelmingly remained in the theoretical realm and estimation exercises have been rare. Farmer and Guo (1995) is an early attempt to estimate a sunspot model using classical simultaneous equations methods. It is only Pintus et al. (2016) and Pavlov and Weder (2017) who perform full-information Bayesian estimations as in the present paper. Pintus et al. (2016) build a model with financial market frictions and loan contracts that are arranged with variable-rates of interest. The model's indeterminacy affects the propagation mechanism in particular of (fundamental) financial shocks. These shocks then explain about one quarter of business cycles fluctuations. Financial markets are not featured in Pavlov and Weder (2017) and their study excludes the Great Recession. Lastly, while the exact definitions of confidence do not completely overlap, our result also parallels Angeletos et al. (2016) and Milani (2017) who maintain that sentiment swings drive a large fraction of U.S. aggregate fluctuations.

Next, we will lay out the artificial economy. This is followed by the presentation of the estimation, discussions of results and various robustness checks. Finally, we provide a theory of the Great Recession.

2 The Model

The artificial economy features credit frictions in the form of endogenous borrowing constraints in a model of monopolistic competition in which, as usual, perfectly competitive firms produce the final output by combining a continuum of differentiated intermediate inputs. Intermediate goods 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 frequently considered as key drivers of business cycles. Time proceeds in discrete steps. The model's discussion will be relatively brief and it will concentrate on the alterations to Benhabib and Wang (2013).

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. The firms rent the two factor services 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 the differentiated varieties. The monopolistic competitive firms generate profits by charging a mark-up over marginal costs. Following Barth and Ramey (2001) who report that a substantial portion of U.S. firms raise working capital, we assume that firms' two variable inputs must be financed by short-run loans. 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 $B_t(i)$ and it is constrained by the value of the collateral, which is the firms' pledge of the period-earnings, i.e.

$$B_t(i) = w_t N_t(i) + r_t \kappa_t(i) \leq \theta_t \xi_t P_t(i) Y_t(i).$$

Under this credit constraint, if there is a default event, the lender has the right to recover a fraction of the firm's end-of-period revenues $P_t(i)Y_t(i)$.[3] The model features two financial frictions and their product $\theta_t \xi_t$ represents the artificial economy's financial tightness. Concretely, ξ_t refers to an endogenous credit constraint: the borrowing constrictions vary with the aggregate state of economic activity which reflects creditors' ability to pay back loans. In particular, ξ_t is an increasing function of the deviation of actual output Y_t from balanced-growth output $\overline{Y}_t$

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

in which we restrict the parameter to $0 < \tau < 1$ and $\gamma > 0$, an assumption in line with Figure 1. The parsimonious formulation of ξ_t entails many micro-founded makeups without the need to confine itself to a particular one.[4] For example, it can stand in for Benhabib and Wang's (2013) setup with fixed liquidation costs or ξ_t can also describe how market conditions determine the probability that lenders can recover as well as resell collateral. In addition to the endogenous component, exogenous disturbances θ_t affect financial health. These shocks originate in the financial sector as in Jermann and Quadrini (2012) or Liu et al. (2013). The exogenous collateral or

[3] Unlike in the original Benhabib and Wang (2013) model, our setup does not include fixed liquidation costs. Indeterminacy still holds. When we compare the two models using the Bayesian estimation method, we find that the model without fixed costs is favored by the data.

[4] Eisfeldt and Rampini (2006) offer some evidence about the cyclical properties of ξ_t.

financial 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 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

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

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

2.2 Preferences

Households are represented by an agent with the lifetime utility

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

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 φ denotes the disutility of working. The term Φ_t represents perturbations to the agent's utility of consumption that generate urges to consume, as in Baxter and King (1991) and Weder (2006). This aggregate demand shock comes in two parts. One grows along with economy's consumption trend X_t^Y and the other one part is a transitory shock that follows the autoregressive process

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

with $\varepsilon_{\Delta,t} \backsim N(0, \sigma_{\Delta}^2)$ and so that $\Delta_t = \Phi_t / X_t^Y$. This shock is also one of the drivers of 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 wider interpretation than mere shocks to preferences. A more agnostic reading includes, for example, wage or price stickiness, 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

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

with the shock's variance σ_g^2.

2.4 Equilibrium and steady state

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

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

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

$$\phi_t = \theta_t \xi_t = \tau \theta_t \left(\frac{Y_t}{\overline{\overline{Y}}_t} \right)^{\gamma}.$$

In the steady state, τ equals marginal costs ϕ, i.e. the inverse of the markup, thus this parameter is not free. In addition, stationarity conditions restrict $\xi = \phi$.

2.5 Self-fulfilling dynamics

The detrended and linearized economy is solved numerically (using standard parameters as listed in Table 1). We assume a certain degree of market power such that the credit constraint is always binding, i.e. $\phi_t^{-1} > \frac{\lambda}{\lambda-1}$. Figure 2 maps the local dynamics' zones in the $\gamma - \phi^{-1}-$space. If the credit limit is close to constant, i.e. the parameter γ is small, the economy's dynamics are unique. However, combinations of market power and a procyclical credit limit delivers indeterminacy. The indeterminacy mechanism operates via an upwardly sloping wage-hours locus similar to many animal spirits models.[5] Then, how can, say, pessimistic expectations about the future create problems? The storyline would go as follows: 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 outwards. But their pessimistic expectations will also lead households to decrease the lending to firms. This contraction of credit will tighten the firms' borrowing constraints; given the cost structure, the individual labor demand schedules move leftwards and the markup will rise. 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 and in a drop in aggregate production. In sum, the low animal spirits will be self-fulfilling.

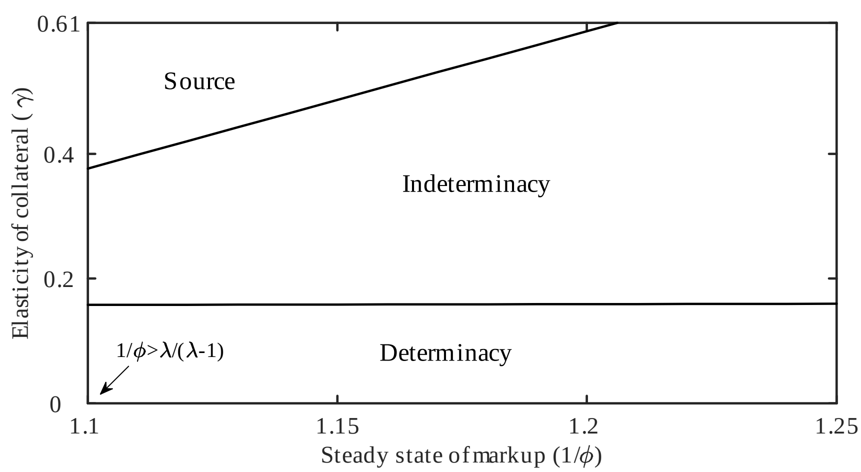

Figure 2: Parameter spaces of dynamics.

[5]See for example, Farmer and Guo (1994) or Wen (1998).

Is this underlying mechanism that leads to indeterminacy empirically plausible? Phrased alternatively, are markups countercyclical and loans procyclical? The markup's countercyclical pattern is widely established (Rotemberg and Woodford, 1991, for example). Figure 3 plots the growth rates of both Commercial and Industrial Loans (all Commercial Banks) along with GDP growth. The two series show high conformity that leads us to conclude that loans are procyclical. This suggests to us that the indeterminacy mechanism is not at odds with stylised facts of the business cycle.

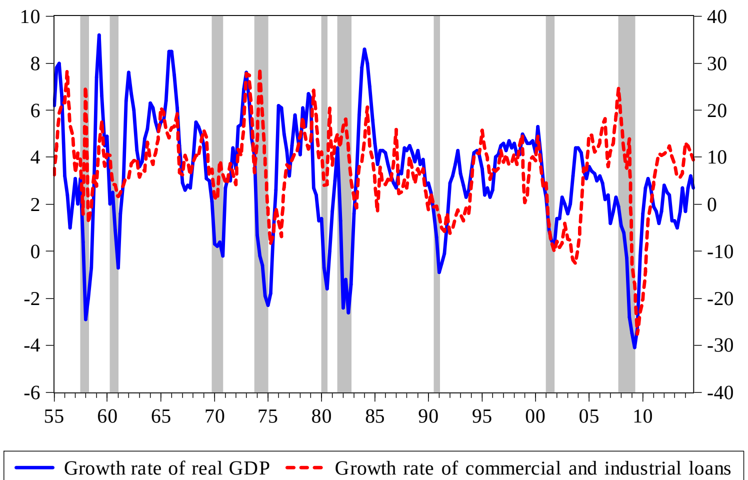

Figure 3: Growth rates of U.S. GDP and Commercial and Industrial Loans (on right-hand scale). Shaded areas indicate NBER recessions.

3 Estimation

Our next step is to discuss how animal spirits are introduced into the model, to present the data that is employed in the analysis, as well as to outline the full information Bayesian estimation of the artificial economy. We quantify the contribution of animal spirits shocks to business cycle fluctuations. Finally, we compare the estimated shocks to corresponding empirical measures.

3.1 Animal spirits in the rational expectations model

If there are many rational expectations equilibria in the model economy, this continuum is a device to introduce animal spirits. In fact, we treat them as quasi-fundamentals as they select from the many possible outcomes. Concretely, we break down the forecast error of output in the linearized model

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

(hats denote percentage deviations from steady states) into five fundamental and one non-fundamental components, as suggested by Lubik and Schorfheide (2003):

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

The parameters Ω_x, Ω_a, Ω_Δ, Ω_g and Ω_θ determine the effect of technological progress, investment-specific technology, preferences, government spending and collateral shocks on the expectations error. This break-down leaves the belief shock ε_t^b as a residual. The last equation then promulgates a strict definition of animal spirits: they are orthogonal to the other disturbances, thus independent of economic fundamentals.

3.2 Data and measurement equation

The estimation uses quarterly U.S. data running from 1955:I to 2014:IV and includes seven observable time series: (i) the log difference of real per capita GDP, (ii) real per capita consumption, (iii) real per capita investment, (iv) real per capita government spending, (v) the relative price of investment, (vi) the log difference of per capita hours worked from its sample mean, as well as (vii) the credit spread from its sample mean. Financial market frictions in the model are $\theta_t \xi_t$.[6] We instrument

[6] It may seem perhaps more intuitive to construct a counterpart of credit spread in the model (which has not intertemporal debt) via the Lagrangian multiplier of the working capital constraint. However, this multiplier is a linear function of the financial frictions, thus, the estimation results would be identical.

them by a credit spread similar to Christiano et al. (2014). In particular, Christiano et al. make use of the difference between the interest rate on Baa corporate bonds and the ten-year US government bond rate. The Appendix provides the full description of the data used and its construction. The corresponding measurement equation is

$$\begin{bmatrix} \ln Y_t - \ln Y_{t-1} \\ \ln C_t - \ln C_{t-1} \\ \ln A_t I_t - \ln A_{t-1} I_{t-1} \\ \ln G_t - \ln G_{t-1} \\ \ln A_t - \ln A_{t-1} \\ \ln N_t - \ln \overline{N} \\ \text{credit spread} \end{bmatrix} = \begin{bmatrix} \widehat{y}_t - \widehat{y}_{t-1} + \widehat{\mu}_t^y \\ \widehat{c}_t - \widehat{c}_{t-1} + \widehat{\mu}_t^y \\ \widehat{i}_t - \widehat{i}_{t-1} + \widehat{\mu}_t^y \\ \widehat{g}_t - \widehat{g}_{t-1} + \widehat{a}_t^g - \widehat{a}_{t-1}^g + \widehat{\mu}_t^y \\ \widehat{\mu}_t^a \\ \widehat{N}_t \\ -x * \tau * (\gamma \widehat{y}_t + \widehat{\theta}_t) \end{bmatrix} + \begin{bmatrix} \ln \mu^y \\ \ln \mu^y \\ \ln \mu^y \\ \ln \mu^y \\ \ln \mu^a \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t}^{me} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \varepsilon_{s,t}^{me} \end{bmatrix}$$

where $a_t^g \equiv X_t^G / X_t^Y = (a_{t-1}^g)^{\psi_{yg}} (\mu_t^y)^{-1}$. In the last measurement equation, 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. Both output growth and credit spread are measured with errors $\varepsilon_{y,t}^{me}$ and $\varepsilon_{s,t}^{me}$ which are i.i.d. innovations with mean zero and standard deviation σ_y^{me} and σ_s^{me}, respectively. Allowing for a measurement error to output is a way to circumvent stochastic singularity (e.g. Schmitt-Grohé and Uribe, 2012). The measurement error to the spread can reconcile any mis-measurement in the data, especially since only a proxy is observed (e.g. Justiniano et al., 2011). Both measurement errors are restricted to absorb no more than ten percent of the variance of the corresponding observables. We estimate the model by allowing all fundamental and the animal spirits shocks to matter.

3.3 Calibrations and priors

We group the model parameters into two categories: calibrated and estimated. The first set of parameters is calibrated following the literature and is based on national accounts data averages. We only address some of these calibrations (all are listed in completion 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, G/Y, is calibrated at 21 percent, a number which matches national accounts average. The quarterly growth rates of per capita output μ^y and the relative price of investment μ^a are set equal to their sample averages of 1.0041 and 0.9949. Finally, the household's first-order conditions determine the elasticity of the depreciation rate from $\nu = (\mu^k/\beta - 1)/\delta$, where $\mu^k = \mu^y/\mu^a$ is the gross growth rate of capital.

Table 1: Calibration

Parameters	Values	Description
β	0.99	Subjective discount factor
α	1/3	Capital share
η	0	Labor supply elasticity parameter
λ	10	Elasticity of substitution between goods
δ	0.0333	Steady-state depreciation rate
u	1	Steady-state capacity utilization rate
G/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

All other model parameters are estimated. Our prior assumptions are summarized in Table 2. The parameters estimated here include the steady state marginal cost ϕ (or equivalently the inverse of the mark-up), the elasticity of collateral γ, the scale parameter x, the parameters that describe the stochastic processes and the standard deviation of the measurement error. Standard deviations are in percent terms. 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 eleven to twenty 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, De Loecker and Eeckhout, 2017, and Eggertsson et al., 2018). Second, the upper value of ϕ is further restricted by the inequality constraints

Table 2: Estimation

Estimated parameters	Prior distribution: Range	Prior distribution: Density[mean,std]	Posterior distribution: Mean	Posterior distribution: 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, γ	[0.160,0.607]	Uniform	0.322	[0.315,0.329]
Gov. trend smoothness, ψ_{yg}	[0,1)	Beta[0.5,0.2]	0.965	[0.953,0.977]
Scale parameter, x	R^+	IGam[44,Inf]	47.33	[44.28,50.46]
AR technology shock, ρ_x	[0,1)	Beta[0.5,0.2]	0.025	[0.008,0.041]
AR investment shock, ρ_a	[0,1)	Beta[0.5,0.2]	0.029	[0.013,0.045]
AR preference shock, ρ_Δ	[0,1)	Beta[0.5,0.2]	0.984	[0.981,0.988]
AR government shock, ρ_g	[0,1)	Beta[0.5,0.2]	0.986	[0.982,0.989]
AR collateral shock, ρ_θ	[0,1)	Beta[0.5,0.2]	0.992	[0.990,0.994]
Belief shock volatility, σ_b	R^+	IGam[0.1,Inf]	0.640	[0.615,0.665]
SE technology shock, σ_x	R^+	IGam[0.1,Inf]	0.690	[0.646,0.733]
SE investment shock, σ_a	R^+	IGam[0.1,Inf]	0.562	[0.525,0.598]
SE preference shock, σ_Δ	R^+	IGam[0.1,Inf]	0.386	[0.364,0.407]
SE government shock, σ_g	R^+	IGam[0.1,Inf]	0.944	[0.896,0.992]
SE collateral shocks, σ_θ	R^+	IGam[0.1,Inf]	0.132	[0.121,0.143]
SE measurement error, σ_y^{me}	[0,0.29]	Uniform	0.290	[0.289,0.290]
SE measurement error, σ_s^{me}	[0,27.42]	Uniform	27.28	[27.11,27.42]
Technology shock effect, Ω_x	[-3,3]	Uniform	-0.514	[-0.590,-0.438]
Investment shock effect, Ω_a	[-3,3]	Uniform	0.271	[0.176,0.367]
Preference shock effect, Ω_Δ	[-3,3]	Uniform	0.872	[0.756,0.994]
Government shock effect, Ω_g	[-3,3]	Uniform	0.256	[0.205,0.305]
Collateral shock effect, Ω_θ	[-3,3]	Uniform	0.999	[0.610,1.393]
Log-data density		4064.98		

$\xi\frac{\lambda-1}{\lambda} < \phi < \frac{\lambda-1}{\lambda}$ for the financial constraint to bind.[7] We set the prior mean for x to match the standard deviation of the smoothed endogenous financial frictions in the model without any financial information (data and shock) and the standard deviation of the demeaned spread data. We adopt an inverse gamma distribution for the prior. For the persistence parameters we use a beta distribution and the standard deviations of the shocks follow an inverse gamma distribution. The prior distributions for the expectational parameters Ω_x, Ω_a, Ω_Δ, Ω_g and Ω_θ are uniform, thus agnostic about their values. Endogenous priors prevent overpredicting the model variances as in

[7] The prior distribution of γ guarantees that the complete indeterminacy region is covered. Since we concentrate on this region, during the MCMC, all proposed draws from the determinacy and source regions were discarded.

Christiano et al. (2011). We use the Metropolis-Hastings algorithm to generate one million draws from the posterior for each of the two chains, discard the initial half of the draws as burn-in, and adjust the scale in the jumping distribution to achieve a 25 to 30 percent acceptance rate for each chain.

3.4 Estimation results

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. Disturbances to preference, government spending and collateral 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 (band-pass filtered)

	Data			Model		
x	σ_x/σ_Y	$\rho(x,Y)$	ACF	σ_x/σ_Y	$\rho(x,Y)$	ACF
Y_t	1.00	1.00	0.93	1.00	1.00	0.91
C_t	0.58	0.85	0.92	0.63	0.75	0.90
I_t	3.25	0.89	0.94	3.09	0.88	0.92
G_t	0.99	0.01	0.94	0.96	0.21	0.90
N_t	1.24	0.87	0.94	1.01	0.98	0.92

Table 3 reports second moments of the main macroeconomic variables calculated using U.S. data and compares these moments to those obtained from model simulations at the posterior mean, both at business cycle frequencies. The model matches fairly well the relative standard deviations, autocorrelations and the variables' cross-correlations with output.[8] Table 4 displays the contribution of each

[8] The model does not capture the standard deviations and autocorrelations perfectly because i) the estimator tries to match the entire autocovariance function of the data and ii) the estimation

structural shock, which we list in the top row, to the variances of key macroeconomic variables. Through the lens of our theory, the decomposition suggests that animal spirits shocks ε_t^b are a major source of U.S. aggregate fluctuations. These shocks account for over 40 percent of output growth fluctuations. The ensemble of other aggregate demand shocks plays 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. The credit spread is mainly driven by stochastic financial factors as well as by the three demand side disturbances (i.e. animal spirits, preferences and government spending).[9]

Table 4: Unconditional variance decomposition

Series/shocks	ε_t^b	ε_t^x	ε_t^a	ε_t^Δ	ε_t^g	ε_t^θ	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln(Y_t/Y_{t-1})$	43.43	11.17	5.72	15.70	9.93	6.71	6.80	0.00
$\ln(C_t/C_{t-1})$	6.18	40.42	2.76	39.84	1.96	8.82	0.00	0.00
$\ln(A_t I_t/A_{t-1} I_{t-1})$	66.53	2.41	7.06	9.34	7.09	7.57	0.00	0.00
$\ln(N_t/\overline{N})$	21.24	2.54	9.37	26.50	22.06	18.30	0.00	0.00
$\ln(G_t/G_{t-1})$	0.00	0.98	0.16	0.00	98.85	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	12.26	2.06	4.85	17.99	15.06	43.49	0.00	3.30

In sum, the estimation suggests that psychological motivations are behind a significant portion of the fluctuations in U.S. aggregate real economic activity. While the definitions of confidence shocks do not exactly overlap, this result parallels recent findings by Angeletos et al. (2016), Milani (2017) and Nam and Wang (2016) who, while arguing within theoretical frameworks that involve uniqueness, also find that bouts of optimism and pessimism are driving a large fraction of U.S. aggregate fluctuations.

was done using variables in growth rates but we instead report variables' fluctuations at business cycle frequencies.

[9]We estimate the model using loan data and animal spirits remain significant. Furthermore, variance decompositions at business cycle frequencies deliver almost identical results.

3.5 Are shocks meaningfully labeled?

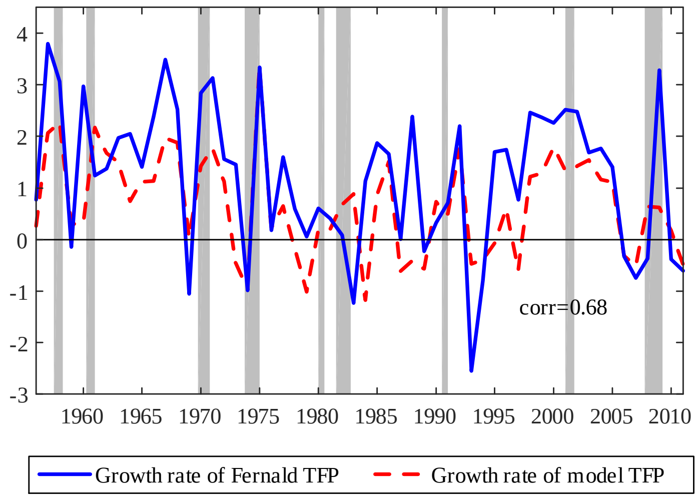

Figure 4: Fernald's vs model's total factor productivity (annual data).

We identify the shocks by estimating in a system and it is thus fair to ask if the estimated shocks are meaningfully labelled. Specifically, 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 (TFP) series is compared with Fernald's (2014) TFP series for the United States.[10] Fernald's TFP 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 of this exogenous validation are reassuring as shown in Figure 4. Both productivity series not only have similar amplitudes, but their contemporaneous correlation comes in at 0.68. Hence, the model is successful in extracting productivity shocks.[11] Next, Figure 5 compares the index of estimated confidence and the U.S. Business Confidence index (band-pass filtered to concentrate on the relevant frequencies). Clearly, the empirical confidence index is influenced by a raft of fundamentals and non-fundamentals, thus, it is not exactly clear how the

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

[11] We also plot the respective quarterly series in the Appendix' Figure 9.

empirical data would map our theoretical notion of animal spirits. Yet, one would expect that the animal spirits and confidence data display a certain similarity. In fact, the two sentiment series are strongly correlated and we interpret the relationship in Figure 5 as endorsing our estimation and as supporting the case that estimated belief shocks reflect variations in people's expectations about the future path of the economy.[12]

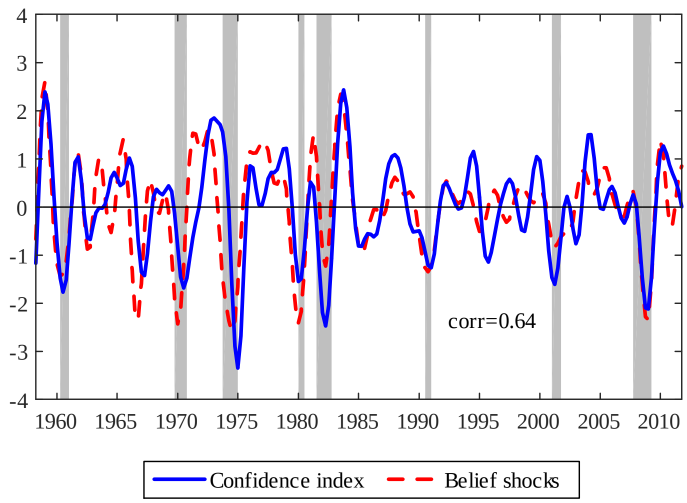

Figure 5: Business confidence index vs animal spirits shocks (normalized data).

4 Robustness checks

In this Section, we report several robustness checks. First, we leave Lubik and Schorfheide's (2003) representation of a belief shock and follow Farmer et al.'s (2015) formulation. Next, we go through alternative observables to measure financial markets' health. This is followed by adding Fernald's (2014) TFP data to the observables. We also replace permanent technology shocks by transitory shocks and consider the presence of shocks to the marginal efficiency of investment as in Justiniano et al. (2011). Lastly, we will introduce a pure labor supply shock.

[12]The correlation of the estimated sunspot shocks and Fernald's TFP series is insignificant at 0.2.

Table 5: Posterior distribution comparison

	Model with $\eta_t^y = \varepsilon_t^b$			
	Prior distribution		Posterior distribution	
Parameters	Range	Density[mean,std]	Mean	90% Interval
ϕ	[0.83,0.90]	Beta[0.88,0.01]	0.833	[0.831,0.834]
γ	[0.160,0.607]	Uniform	0.322	[0.315,0.329]
ψ_{yg}	[0,1)	Beta[0.5,0.2]	0.965	[0.954,0.977]
x	R^+	IGam[44,Inf]	47.30	[44.18,50.35]
ρ_x	[0,1)	Beta[0.5,0.2]	0.025	[0.008,0.042]
ρ_a	[0,1)	Beta[0.5,0.2]	0.029	[0.014,0.045]
ρ_Δ	[0,1)	Beta[0.5,0.2]	0.984	[0.981,0.988]
ρ_g	[0,1)	Beta[0.5,0.2]	0.986	[0.982,0.989]
ρ_θ	[0,1)	Beta[0.5,0.2]	0.992	[0.990,0.994]
σ_η	R^+	IGam[0.1,Inf]	0.862	[0.821,0.902]
σ_x	R^+	IGam[0.1,Inf]	0.690	[0.647,0.733]
σ_a	R^+	IGam[0.1,Inf]	0.562	[0.525,0.598]
σ_Δ	R^+	IGam[0.1,Inf]	0.385	[0.364,0.407]
σ_g	R^+	IGam[0.1,Inf]	0.945	[0.897,0.993]
σ_θ	R^+	IGam[0.1,Inf]	0.132	[0.121,0.143]
σ_y^{me}	[0,0.29]	Uniform	0.290	[0.289,0.290]
σ_s^{me}	[0,27.42]	Uniform	27.28	[27.11,27.42]
$\rho(\varepsilon^x, \eta^y)$	[-1,1]	Uniform	-0.406	[-0.465,-0.349]
$\rho(\varepsilon^a, \eta^y)$	[-1,1]	Uniform	0.172	[0.110,0.233]
$\rho(\varepsilon^\Delta, \eta^y)$	[-1,1]	Uniform	0.388	[0.338,0.438]
$\rho(\varepsilon^g, \eta^y)$	[-1,1]	Uniform	0.275	[0.226,0.327]
$\rho(\varepsilon^\theta, \eta^y)$	[-1,1]	Uniform	0.151	[0.091,0.213]
Log-data density		4066.02		

We begin the chain of robustness checks by following the approach of Farmer et al. (2015) in which the animals spirits shock is simply the forecast error, i.e. $\eta_t^y = \varepsilon_t^b$, with a variance σ_η^2. Intuitively, since output is forward looking, this expectation error should be correlated with fundamental shocks. Yet, it is also a sunspot shock, as it can cause movements in economic activity without any shifts to fundamentals. Assuming a uniform distribution, we thus estimate the correlations between η_t^y and the fundamental shocks. The priors for the other parameters are kept the same as in the baseline model. As can be seen by comparing Tables 2 and 5, our estimation results are robust to the formation of the expectation error. The posterior distributions are almost identical and the closeness of the log-data densities confirms that the goodness of fit between the models is equivalent.[13]

The next robustness check concerns the choice of the observed spread when instrumenting financial markets' conditions as we consider the sensitivity to using various alternative spreads. In particular, we ask if using the Baa-Aaa spread or the Baa-Federal funds rate spread leads to significantly different results in the estimation. We report the variance decompositions only. The results for the alternative spreads are documented in Tables 6 and 7. Animal spirits continue to stand out as the main driver of the business cycle.[14]

Table 6: Unconditional variance decomposition (Baa-Aaa spread)

Series/shocks	ε_t^b	ε_t^x	ε_t^a	ε_t^Δ	ε_t^g	ε_t^θ	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln(Y_t/Y_{t-1})$	45.46	11.34	5.34	15.63	9.12	6.31	6.80	0.00
$\ln(C_t/C_{t-1})$	6.67	41.08	2.65	38.98	1.84	8.78	0.00	0.00
$\ln(A_tI_t/A_{t-1}I_{t-1})$	68.22	2.32	6.45	9.04	6.24	7.73	0.00	0.00
$\ln(N_t/\overline{N})$	23.25	2.31	9.08	25.25	20.31	19.79	0.00	0.00
$\ln(G_t/G_{t-1})$	0.00	1.07	0.17	0.00	98.76	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	13.12	1.87	4.59	16.51	13.48	47.13	0.00	3.30

[13] Second moments and variance decompositions are virtually identical and are not presented to conserve space. The Appendix shows robustness to constructing belief shocks using forecast errors of other variables.

[14] We considered other interest spreads and the results repeat.

Table 7: Unconditional variance decomposition (Baa-FF spread)

Series/shocks	ε_t^b	ε_t^x	ε_t^a	ε_t^Δ	ε_t^g	ε_t^θ	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln(Y_t/Y_{t-1})$	42.35	12.38	6.10	17.45	9.40	4.97	7.34	0.00
$\ln(C_t/C_{t-1})$	5.93	43.61	3.01	39.50	1.86	6.09	0.00	0.00
$\ln(A_t I_t/A_{t-1} I_{t-1})$	65.43	2.62	7.51	10.04	7.00	7.40	0.00	0.00
$\ln(N_t/\overline{N})$	22.11	2.33	10.53	26.72	22.55	15.76	0.00	0.00
$\ln(G_t/G_{t-1})$	0.00	1.02	0.17	0.00	98.81	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	14.32	2.19	6.08	20.38	17.16	34.61	0.00	5.26

Next, we add total factor productivity to the catalog of observables. Fernald's (2014) data is the natural series to choose from. Fernald adjusts for variations in factor utilization (labor and capital) and includes adjustment for quality or composition of inputs. Most of these influences are not part of the present artificial economy and we thus add one more measurement error on total factor productivity (at not more than ten percent). Table 8 shows that the previous results remain robust. Animal spirits continue to cause the bulk of U.S. output fluctuations. The technology shocks' contributions are lower, with a best point estimate near ten percent.

Table 8: Unconditional variance decomposition (Fernald TFP)

Series/shocks	ε_t^b	ε_t^x	ε_t^a	ε_t^Δ	ε_t^g	ε_t^θ	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$	$\varepsilon_{tfp,t}^{me}$
$\ln(Y_t/Y_{t-1})$	39.02	10.35	5.10	12.63	9.13	17.01	6.77	0.00	0.00
$\ln(C_t/C_{t-1})$	4.63	38.01	2.18	34.21	1.49	19.48	0.00	0.00	0.00
$\ln(A_t I_t/A_{t-1} I_{t-1})$	59.56	2.09	6.31	8.56	6.12	17.36	0.00	0.00	0.00
$\ln(N_t/\overline{N})$	16.00	2.35	7.14	21.74	16.70	36.07	0.00	0.00	0.00
$\ln(G_t/G_{t-1})$	0.00	1.08	0.15	0.00	98.76	0.00	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
Credit spread	6.54	1.34	2.61	10.38	8.13	67.28	0.00	3.71	0.00
$\ln(TFP_t/TFP_{t-1})$	0.00	92.29	0.00	0.00	0.00	0.00	0.00	0.00	7.71

So far, we have assumed that technology follows a stochastic trend. We now replace permanent technology shocks by transitory shocks. Hence, the production technology is given by

$$Y_t = Z_t K_t^{\alpha} (\mu^t N_t)^{1-\alpha}$$

and the growth rate of labor augmenting technological progress is deterministic at the constant rate μ, as in King et al. (1988). We permit temporary changes in total factor productivity through Z_t, which follows a first-order autoregressive process

$$\ln Z_t = (1-\rho_z)\ln Z + \rho_z \ln Z_{t-1} + \varepsilon_{z,t} \qquad 0 < \rho_z < 1.$$

The presence of (one more) transitory shock will also make it (even) harder for animal spirits shocks to explain data's transitory fluctuations. Nevertheless, the model estimation delivers similar posterior means of the parameters as the baseline estimation and they are reported in the Appendix. Noteworthy is the estimate for ρ_z at 0.997 which is arguably very close to a unit root. While high, this number is consistent with Ireland (2001), for example. The variance decompositions of the stationary technology shocks model are reported in Table 9. Technology shocks account for about 17 percent of GDP volatility. Animal spirits remain the most critical driver of aggregate fluctuations and they continue to explain roughly 40 percent of output growth variations.[15]

Table 9: Unconditional variance decomposition (transitory TFP)

Series/shocks	ε_t^b	ε_t^z	ε_t^a	ε_t^Δ	ε_t^g	ε_t^θ	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln(Y_t/Y_{t-1})$	39.18	16.79	5.28	15.64	8.21	8.69	6.22	0.00
$\ln(C_t/C_{t-1})$	3.78	43.19	2.19	40.98	1.13	8.73	0.00	0.00
$\ln(A_t I_t/A_{t-1} I_{t-1})$	57.92	11.81	6.28	10.25	5.64	8.10	0.00	0.00
$\ln(N_t/\overline{N})$	16.08	17.47	8.35	26.25	15.10	16.75	0.00	0.00
$\ln(G_t/G_{t-1})$	0.00	0.00	0.22	0.00	99.78	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	5.63	41.34	2.59	10.61	6.17	30.37	0.00	3.30

[15] The posterior means of the parameters in the model with transitory technology productivity are shown in the Appendix as Table 15. **There, we also report an external validation (Figures 10 and 11) as in Figures 4 and 5 and, again, estimated shocks are very similar to Fernald's series as well as U.S. confidence data.**

The natural question arises which specification of technology is favored by data? This question is answered in Table 10 which compares the model fits of the two alternatively specified models. Data strongly prefers a version of the model in which total factor productivity has a stochastic trend.[16]

Table 10: Model comparison

	Baseline: permanent TFP	Alternative: transitory TFP
Log-data density	4064.98	3811.89

Justiniano et al. (2011) push for shocks that affect the production of installed capital from investment goods or the transformation of savings into the future capital input. This is an alternative way to model exogenous financial frictions. The concept of shocks to the marginal efficiency to investment (MEI) goes back to Greenwood et al. (1988) who formulate the ideas as

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

where we abstract from adjustment costs to not mess with the indeterminacy properties of the artificial economy. The shock ν_t affects the marginal efficiency of capital and it follows an autoregressive process with persistence parameter ρ_ν. The MEI shocks are likely a

> "might proxy for more fundamental disturbances to the intermediation ability of the financial system." [Justiniano et al., 2011, 103]

We estimate the amended model and associate the observed spread with the value of the MEI to impose discipline on the inference of the shock as in Justiniano et al. (2011).[17] Again, we add a measurement error to the spread equation. Table 11

[16]We conduct a similar exercise with respect to the form of the preference shock. Data does strongly prefer the current setup over a version with a stochastic discount factor.

[17]Given the occurrence of financial frictions in two places, we are only able to connect one model friction to the spread's measurement equation. The series of animal spirits remains highly correlation to earlier estimations, thus, our result is not the consequence of putting less restrictions on the psychological shocks.

shows, in line with our previous findings, that the animal spirits shocks remain a most prominent driver of U.S. output fluctuations.[18] An external validation exercise akin to Figures 4 and 5 again finds that estimated shocks are very similar to their empirical counterparts (see Appendix Figures 12 and 13).

Table 11: Unconditional variance decomposition (MEI shock)

Series/shocks	ε_t^b	ε_t^x	ε_t^a	ε_t^Δ	ε_t^g	ε_t^{MEI}	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln\left(Y_t/Y_{t-1}\right)$	46.82	10.15	5.51	15.76	11.18	2.08	8.49	0.00
$\ln\left(C_t/C_{t-1}\right)$	8.77	40.93	2.92	43.77	2.96	0.66	0.00	0.00
$\ln\left(A_t I_t/A_{t-1} I_{t-1}\right)$	69.61	2.35	6.77	9.82	8.68	2.77	0.00	0.00
$\ln\left(N_t/\overline{N}\right)$	25.57	3.62	10.02	31.30	27.17	2.31	0.00	0.00
$\ln\left(G_t/G_{t-1}\right)$	0.00	0.75	0.13	0.00	99.12	0.00	0.00	0.00
$\ln\left(A_t/A_{t-1}\right)$	0.00	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	0.00	0.00	0.00	0.00	0.00	99.95	0.00	0.05

Lastly, we will check if the identified belief shocks are not mistakenly attributed to a mislabeled concept, in particular, if they are not standing in for omitted shocks to labor supply. To do this, we modify the period utility function to

$$\ln C_t - \varphi \Lambda_t \frac{N_t^{1+\eta}}{1+\eta}$$

where now labor supply shocks Λ_t follow

$$\ln \Lambda_t = (1-\rho_\Lambda)\ln \Lambda + \rho_\Lambda \ln \Lambda_{t-1} + \varepsilon_{\Lambda,t} \qquad 0 < \rho_\Lambda < 1.$$

Table 12 demonstrates that this change to preferences does not affect our punchline result: animal spirits shocks remain the main drivers of the U.S. business cycle.

[18] We considered the hypothesis that sunspot shocks are in fact news shocks. In the spirit of Beaudry and Portier (2006), we looked into finding a relation of the belief shocks with future movements of technology. In particular, we compute the correlations of the estimated animal spirits with Fernald's TFP data at four to sixteen quarters out. The correlations are negligible at never more than 0.04.

Table 12: Unconditional variance decomposition (labor supply shock)

Series/shocks	ε_t^b	ε_t^x	ε_t^a	ε_t^Λ	ε_t^g	ε_t^θ	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln(Y_t/Y_{t-1})$	43.24	12.34	5.47	15.59	9.35	6.66	7.36	0.00
$\ln(C_t/C_{t-1})$	6.54	45.36	2.80	34.08	2.00	9.22	0.00	0.00
$\ln(A_tI_t/A_{t-1}I_{t-1})$	66.03	2.55	6.78	10.32	6.97	7.34	0.00	0.00
$\ln(N_t/\overline{N})$	19.42	2.07	8.40	34.16	19.55	16.41	0.00	0.00
$\ln(G_t/G_{t-1})$	0.00	1.01	0.16	0.00	98.84	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	11.15	1.76	4.34	26.36	13.20	38.81	0.00	4.38

5 A closer look at the Great Recession

From 2007 to 2009, the U.S. economy was in a severe slump. The Great Recession was the single-worst economic contraction since the 1930s, with economic activity diving after various financial institutions collapsed. One of the aims of the recent financial friction models is to identify the sources of the crisis. To what extent can animal spirits explain the downturn in GDP observed in this recession?

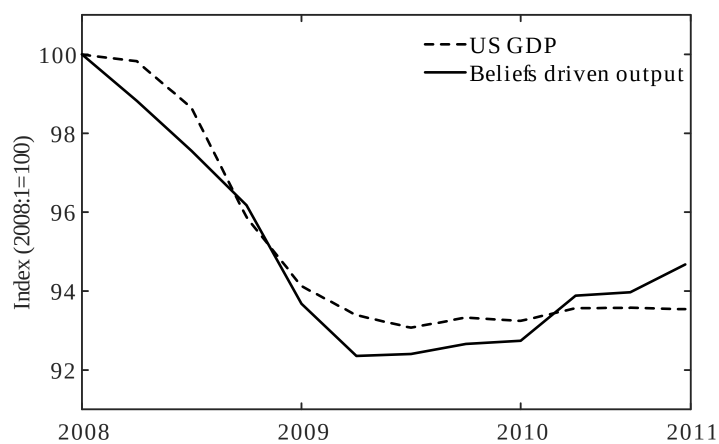

Figure 6: Counterfactual path of output, conditional on estimated belief shocks. Parameters are set at the posterior mean.

We begin with a counterfactual exercise in which we shut down all but the animal spirits shocks (using Section 3's model). Figure 6 plots the counterfactual path of output driven solely by these belief shocks along with the actual series over the Great Recession period. The U.S. data has been detrended by removing long-run productivity trend and also population growth, as we abstract from it in the model. We re-scale both model and U.S. data so that outputs are equal to 100 in 2008:I. The model economy virtually coincides in both timing and depth with the actual economy during the crisis period and the measured drop in confidence can account for most of the decline in output. The counterfactual exercise favors the interpretation that the fall of aggregate output during the Great Recession was closely associated with self-fulfilling beliefs. Our reading of events goes like this: adverse expectations led to a drop in aggregate demand which curbed lending and tightened credit (similar to Kahle and Stulz, 2013). This tightening occurred because people were expecting worsening business conditions and higher defaults. In other words, people became pessimistic and, as a consequence of the effect on financial markets, the reduced investment spending lowered productivity which then made pessimistic expectations self-fulfilled. Our results do not necessarily contradict Christiano et al.'s (2015) account of the Great Recession. Their study finds that the steep decline of aggregate economic activity was overwhelmingly caused by exogenous financial frictions. What our analysis suggests is, however, that it was a drop in people's animal spirits affected aggregate demand and then found its catalyst in financial markets. The endogenous reaction of the financial sector helped in propagating gloomy animal spirits into the full-blown crisis and macroeconomic collapse.

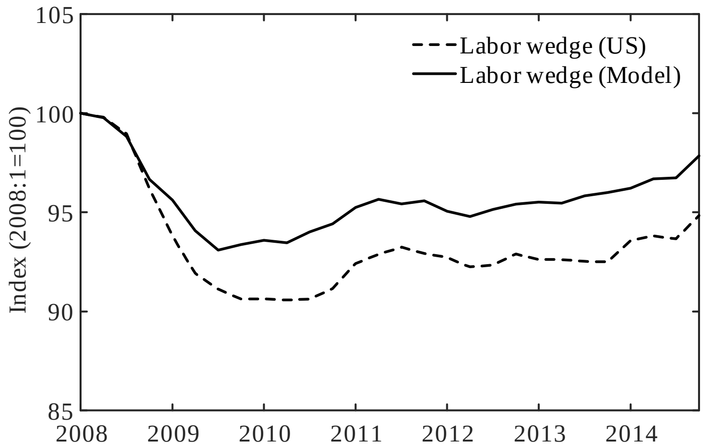

Figure 7: The artificial labor wedge during the Great Recession.

A useful way of thinking about the Great Recession is in terms of Chari et al.'s (2007) business cycle accounting framework which decomposes distortions in the economy into sets of residuals or wedges. When applying this framework, Brinca et al. (2016) assert that

> "[...] considering the period from 2008 until the end of 2011, [our] results imply that the Great Recession in the United States should be thought of as primarily a labor wedge recession, with an important secondary role for the investment wedge." [Brinca et al., 2016, 1042]

This diagnostic finding leads to the question of what would the these wedges look like in the artificial economy? In a benchmark prototype economy, the labor wedge $1-\tau_t^n$ shows up in the budget constraint as

$$... = (1-\tau_t^n)w_t N_t + r_t u_t K_t$$

thus it is like a tax on labor services.[19] The labor wedge is plotted along with its data equivalent in Figure 7. Clearly, the two series show high conformity. The

[19] In the Appendix, we describe the construction of wedges in terms of the artificial economy. Kobayashi and Inaba (2006) prove an equivalence of the capital wedge as well as the investment wedge.

artificial wedge explains about three-fourths of the data wedge's plunge during 2008 and 2009 and it charts a tepid recovery over the 2010 to 2014 period. Our model estimation also suggests an important role for financial market imperfections. Thus, given Brinca et al.'s (2016) assertion, we report a wedge that measures these sort of distortions: it is like a tax on capital income as in Kobayashi and Inaba (2006) or Cavalcanti et al. (2008) and in a benchmark prototype economy it would show up on the right hand side of the budget constraint as $1 - \tau_t^k$:

$$... = w_t N_t + (1 - \tau_t^k) r_t u_t K_t.$$

Figure 8 maps out both the empirical and the model implied capital wedges next to the investment wedge as in Brinca et al. (2016). Note that we report the "τ_ts" rather than the full wedges. These distortions are shown alongside Romer and Romer's (2017) semi-annual index of financial stress which focusses

> "on disruptions to credit supply, rather than on broader conceptions of financial problems" [Romer and Romer, 2017, 3073].

We take three insights from this accounting. Firstly, capital and investment wedges display very similar patterns and they indeed point to a worsening of financial market health after 2007. This mirrors Romer and Romer's (2017) findings. Second, our model lines up well with Brinca et al.'s (2016) interpretation of the Great Recession in terms of both the labor as well as financial wedges. Thirdly, Romer and Romer's (2017) index suggests that financial distress in the U.S. ended by 2011 and this is at some odds with the pattern of both financial wedges which are significantly more persistent. Our take on this picture is that investment spending remained subdued for factors other than financial ones. From our analysis, it appears that the tepid spending reflects a lack of animal spirits, i.e. businesses were not confident about future demand to justify more investment.

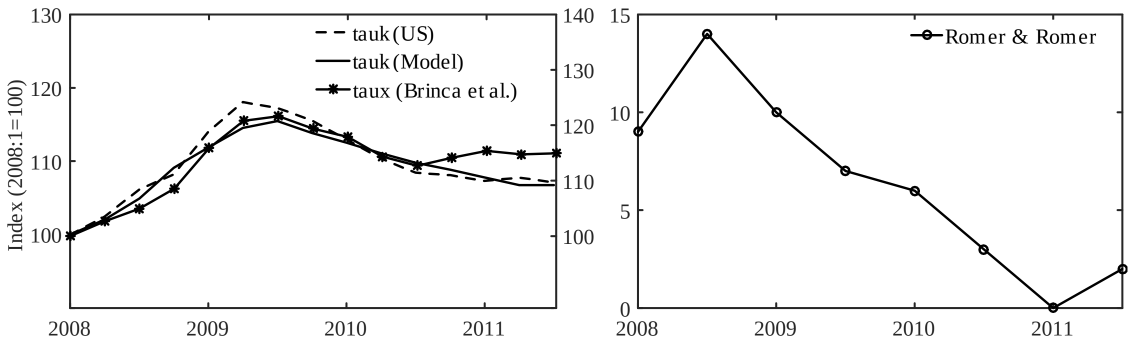

Figure 8: Financial wedges during the Great Recession: the initial observations have been normalized to 100 (capital wedges measured on left-hand axis). Right-hand panel shows Romer and Romer (2017) index.

6 Does data prefer indeterminacy?

So far we have restricted the estimation to the parameter space with multiple equilibria, yet a natural question arises: does data in fact favor a model with indeterminacy? To answer this question, we now estimate the economy over the entire parameter space using the methodology proposed in Bianchi and Nicolò (2017).[20] Their procedure can be implemented without knowing the analytical expressions for the boundaries between the three dynamic regions (recall Figure 2).

The estimation process begins by setting the priors so that determinacy, indeterminacy and source probabilities are at 52:47:1 (in percent). To do this, we adjust the prior of the elasticity of the collateral γ, which is now beta-distributed, to being centered at 0.17 with a standard deviation of 0.1 and truncated to be no more than 0.61.[21] All parameters that pertain to the solution under indeterminacy are restricted to be zero when the estimation for draws is taking place in the determinacy region of the model. Draws from the source region were discarded. In line with

[20] The Appendix explains their methodology in more detail.

[21] All other priors are as above. Details of the estimation procedure are delegated to the Appendix 8.4.

Table 13: Determinacy versus Indeterminacy

	Determinacy	Indeterminacy
Model prior probabilities	0.52	0.47
	Permanent TFP	
Log-data density	3470.07	4065.42
Model posterior probability	0.00	1.00
	Transitory TFP	
Log-data density	3441.67	3812.86
Model posterior probability	0.00	1.00
	MEI	
Log-data density	3601.05	4305.71
Model posterior probability	0.00	1.00
	Labor supply shocks	
Log-data density	3122.67	4001.61
Model posterior probability	0.00	1.00

Bianchi and Nicolò (2017), we follow the approach proposed in Farmer et al. (2015) and construct the forecast errors of output η_t^y as a belief shock with variance σ_η^2 and allow the expectation errors to be correlated with the fundamental shocks. As would be reasonable, for these correlations we assume flat priors that are uniform between -1 and 1. Table 13 presents the results for model versions discussed earlier involving i) permanent technology shocks, ii) transitory technology shocks, iii) shocks to the marginal efficiency to investment and iv) labor supply shocks. The observable variables are the same as in Sections 3 and 4. The log data densities in Table 13 suggest that U.S. data strongly favours the indeterminacy model over all three versions of the economy in which animal spirits cannot play a role.

Three further observations are worthwhile mentioning. First, the estimated parameters under indeterminacy that arise when we implement the methodology developed in Bianchi and Nicolò (2017) are essentially equivalent to our previous results. Thus, estimating via their procedure leaves results unaffected and the implications regarding the important role of animal spirits carry over (see for example Table 16 in the Appendix). Second, in addition to being favored by data, the indeterminacy model is superior in identifying shocks for which empirical counterparts exist. For example, the model-based technology shocks track the empirical TFP series better under indeterminacy: when comparing the estimated sequence as done in the external validation of Figure 4, then the contemporaneous correlation with Fernald's series drops slightly from 0.68 to 0.65 under determinacy. Third, the key difference in the parameter estimates across the two regions applies to the parameter γ that controls the endogenous component of credit market tightness: γ approaches zero for the determinacy versions of the model. The endogenous aspect of the collateral constraint disappears.

How can we make sense of the finding that the indeterminacy model is preferred by U.S. data? The absence of the endogenous feedback of financial market conditions to the state of the economy implies that other fundamental shocks' amplification mechanisms are curtailed and movements of the collateral constraint (and of marginal costs) are determined by the exogenous financial friction shocks. For example, as is shown in the Appendix' Table 17, under determinacy the MEI shock explains about thirty percent of output fluctuations and the spread's variations in almost their entirety. These numbers are quite similar to Justiniano et al. (2011, Table 4) while at somewhat different frequencies. However, the rigid collateral constraints imply that the other fundamental shocks are no longer able to contribute towards the procyclical variations of financial health. In other words, the pattern that was reported in Figure 1 – namely that financial conditions are cyclical and deteriorate during basically all slumps – is more effortlessly accommodated by an artificial economy with an endogenously varying collateral constraint, however, this then implies that the economy becomes indeterminate and, consequently, animal spirits are assigned an important role.

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. Indeterminacy in the model is linked to the empirically observed countercyclical movement of financial market tightness. The artificial economy is driven both by fundamental shocks as well as by animal spirits. U.S. data favours the indeterminacy model over versions of the economy in which sunspots do not play a role. The estimation supports the view that people's animal spirits play a significant role for the U.S. business cycle. Variance decompositions suggest that animal spirits are behind a substantial fraction of output growth variations and they explain an even larger portion of fluctuations in investment spending. Technology shocks and financial frictions shocks are significantly less important in explaining the oscillations in aggregate real economic activity. The 2007-2009 recession appears to have been chiefly caused by adverse confidence shocks.

Admittedly, we have left out various aspects of the economy that could be considered relevant. For example, the economy is real and nominal variables are absent. Thus, we exclude the potential effects of price stickiness and any influence of a monetary authority. Also, the absence of monetary policy as well as the exogenous character of the fiscal side precludes from addressing how policy could potentially influence the dynamics of this economy. The small-scale character of our model, however, provides the advantage of tractability specifically when conducting the various robustness exercises. This being said, mentioned extensions are beyond the scope and the goals of the current paper, but we plan to work out a medium-scale version of the indeterminacy model in the future.

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8 Appendix - for online publication

The Appendix sets out the complete model, a discussion of the wedges, and it lists the data sources and definitions. We begin with collecting the model's equations.

8.1 Model equations and equilibrium dynamics

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

$$\varphi N_t^{\eta} = \frac{1}{C_t - \Phi_t} w_t$$

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

and

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

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 $y_t = Y_t / X_t^Y$, $c_t = C_t / X_t^Y$, $i_t = I_t / X_t^K$, $k_t = K_t / X_{t-1}^K$, $g_t = G_t / X_t^G$, and $y_t / \overline{y}$ approximately equal to $Y_t / \overline{Y}_t$, where $\overline{y}$ represents the steady state of detrended output. The log-linearized system is summarized by

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

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

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

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

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

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

and

$$\widehat{\phi}_t = \gamma\widehat{y}_t + \widehat{\theta}_t.$$

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., $\widehat{y}_t \equiv \log(y_t/\overline{y})$. The last equation shows that if $\gamma \to 0$, then marginal cost and the credit constraint are determined by the exogenous financial shocks only.

8.2 Further robustness checks

Figure 9 compares the smoothed quarterly series of total factor productivity from the estimation vis-vis Fernald's (2014) series. The two sequences are again very similar.

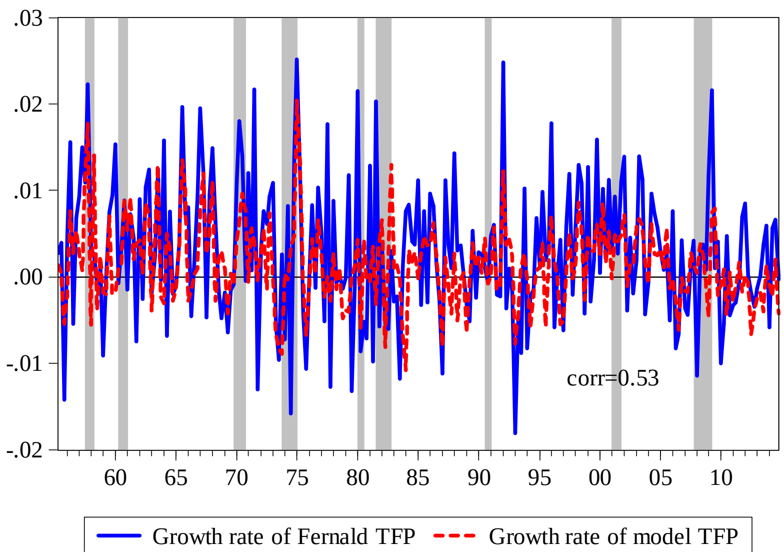

Figure 9: Fernald's vs Model's total factor productivity (quarterly data).

Our baseline estimation attaches the forecast error to the variable output. To test for the robustness of our results, we re-estimate the model but attach the expectations error to consumption, and call it η_t^c. As can be seen by comparing Tables 2 and 14, our estimation results are unaffected: the posterior distributions essentially the same. This parallels the findings in Pavlov and Weder (2017).[22]

Table 14: Posterior distribution comparison

	Alternative model: η_t^c			
	Prior distribution		Posterior distribution	
Parameters	Range	Density[mean,std]	Mean	90% Interval
ϕ	[0.83,0.90]	Beta[0.88,0.01]	0.833	[0.831,0.834]
γ	[0.160,0.607]	Uniform	0.322	[0.315,0.329]
ψ_{yg}	[0,1)	Beta[0.5,0.2]	0.965	[0.953,0.977]
x	R^+	IGam[44,Inf]	47.28	[44.09,50.33]
ρ_x	[0,1)	Beta[0.5,0.2]	0.025	[0.008,0.042]
ρ_a	[0,1)	Beta[0.5,0.2]	0.029	[0.013,0.044]
ρ_Δ	[0,1)	Beta[0.5,0.2]	0.984	[0.981,0.988]
ρ_g	[0,1)	Beta[0.5,0.2]	0.986	[0.982,0.989]
ρ_θ	[0,1)	Beta[0.5,0.2]	0.992	[0.990,0.994]
σ_b	R^+	IGam[0.1,Inf]	0.153	[0.146,0.160]
σ_x	R^+	IGam[0.1,Inf]	0.690	[0.646,0.734]
σ_a	R^+	IGam[0.1,Inf]	0.562	[0.524,0.598]
σ_Δ	R^+	IGam[0.1,Inf]	0.385	[0.364,0.406]
σ_g	R^+	IGam[0.1,Inf]	0.944	[0.895,0.992]
σ_θ	R^+	IGam[0.1,Inf]	0.132	[0.120,0.142]
σ_y^{me}	[0,0.29]	Uniform	0.290	[0.289,0.290]
σ_s^{me}	[0,27.42]	Uniform	27.29	[27.11,27.42]
Ω_x	[-3,3]	Uniform	-0.307	[-0.326,-0.288]
Ω_a	[-3,3]	Uniform	0.341	[0.318,0.363]
Ω_Δ	[-3,3]	Uniform	1.209	[1.179,1.239]
Ω_g	[-3,3]	Uniform	0.061	[0.049,0.073]
Ω_θ	[-3,3]	Uniform	1.556	[1.463,1.649]
Log-data density		4060.58		

[22] Our results are also robust to the formation of forecast error on other jump variables, e.g. marginal cost and variable utilization. To save space, we do not report these findings.

The following table shows the estimation results for transitory technology shocks.

Table 15: Estimation (transitory TFP)

	Prior distribution		Posterior distribution	
Parameters	Range	Density[mean,std]	Mean	90% Interval
ϕ	[0.83,0.90]	Beta[0.88,0.01]	0.832	[0.831,0.833]
γ	[0.160,0.607]	Uniform	0.296	[0.291,0.301]
ψ_{yg}	[0,1)	Beta[0.5,0.2]	0.953	[0.932,0.975]
x	R^+	IGam[44,Inf]	44.38	[42.62,46.24]
ρ_z	[0,1)	Beta[0.5,0.2]	0.997	[0.996,0.998]
ρ_a	[0,1)	Beta[0.5,0.2]	0.020	[0.008,0.032]
ρ_Δ	[0,1)	Beta[0.5,0.2]	0.979	[0.974,0.983]
ρ_g	[0,1)	Beta[0.5,0.2]	0.981	[0.976,0.987]
ρ_θ	[0,1)	Beta[0.5,0.2]	0.992	[0.991,0.994]
σ_b	R^+	IGam[0.1,Inf]	0.662	[0.640,0.685]
σ_z	R^+	IGam[0.1,Inf]	0.321	[0.306,0.334]
σ_a	R^+	IGam[0.1,Inf]	0.564	[0.527,0.600]
σ_Δ	R^+	IGam[0.1,Inf]	0.467	[0.445,0.488]
σ_g	R^+	IGam[0.1,Inf]	0.943	[0.894,0.992]
σ_θ	R^+	IGam[0.1,Inf]	0.145	[0.133,0.156]
σ_y^{me}	[0,0.29]	Uniform	0.290	[0.289,0.290]
σ_s^{me}	[0,27.42]	Uniform	27.29	[27.12,27.42]
Ω_z	[-3,3]	Uniform	1.054	[0.924,1.187]
Ω_a	[-3,3]	Uniform	0.277	[0.188,0.371]
Ω_Δ	[-3,3]	Uniform	0.729	[0.644,0.818]
Ω_g	[-3,3]	Uniform	0.255	[0.203,0.305]
Ω_θ	[-3,3]	Uniform	1.546	[1.186,1.931]

Figure 10 and 11 show the estimated model's total factor productivity series compared with Fernald's (2014) total productivity series, as well as the index of estimated confidence compared with the U.S. Business Confidence index for the estimation with transitory technology shock.

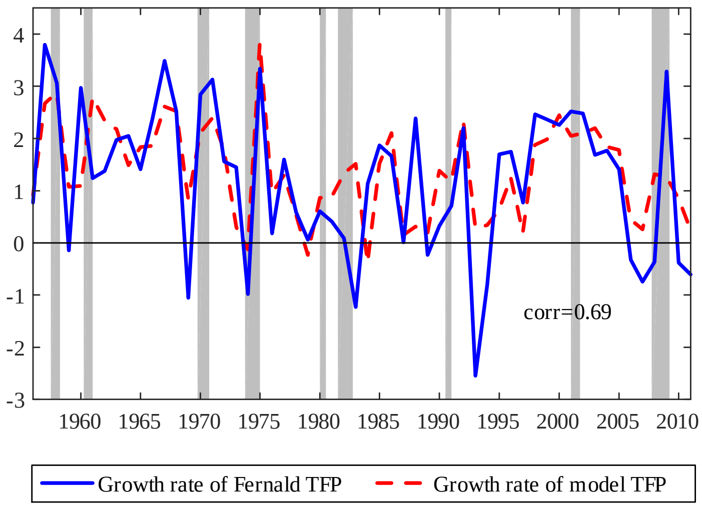

Figure 10: Fernald's vs model's total factor productivity (annual data).

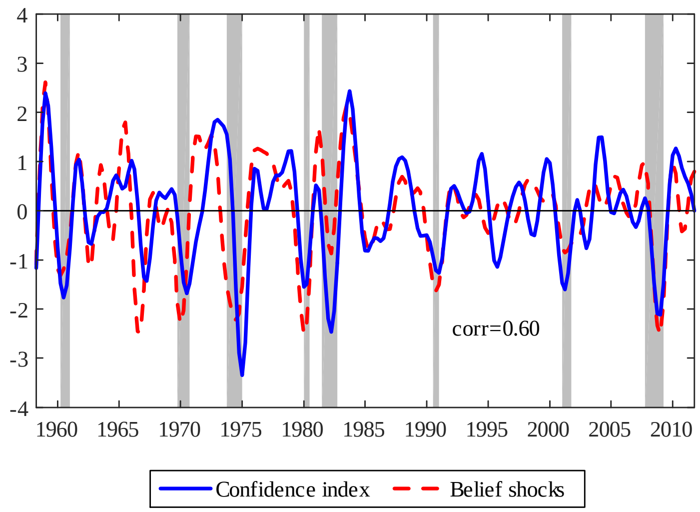

Figure 11: Business confidence index vs animal spirits shocks (normalized data).

Figure 12 and 13 show the estimated model's total factor productivity series compared with Fernald's (2014) total productivity series, as well as the index of estimated confidence compared with the U.S. Business Confidence index for the estimation with MEI shock.

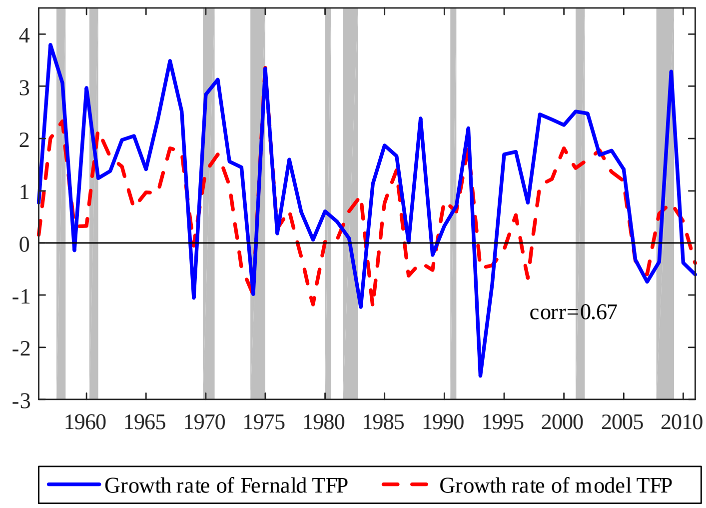

Figure 12: Fernald's vs model's total factor productivity (annual data).

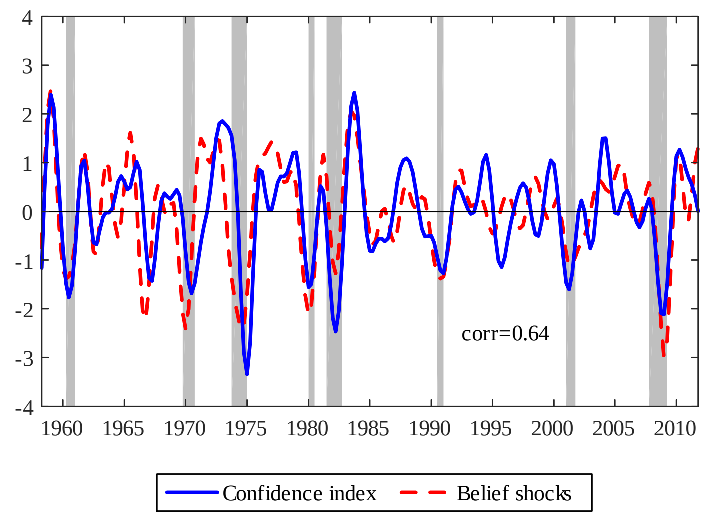

Figure 13: Business confidence index vs animal spirits shocks (normalized data).

8.3 Wedges

Business cycle accounting has been introduced by Chari et al. (2007). Brinca et al.'s (2016) interpretation of the Great Recession in terms of both the labor as well as financial wedges (denoted by τ_t^x). In terms of a benchmark prototype economy, the labor wedge is introduced via the household's period budget constraint

$$... = (1 - \tau_t^n) w_t N_t + r_t u_t K_t.$$

hence it is like a tax on labor services. The labor wedge $1 - \tau_t^n$ is constructed from the intratemporal first-order condition that is a wedge between the marginal rate of substitution and the marginal product of labor. In log-linear form, it would write as

$$\underbrace{(\eta \widehat{N}_t + \widehat{c}_t)}_{\mathrm{MRS}_{C,l}} - \underbrace{(\widehat{y}_t - \widehat{N}_t)}_{\mathrm{MPL}} = \frac{\tau^n}{\tau^n - 1} \widehat{\tau}_t^n.$$

The model's labor wedge is driven by fluctuations of both the markup as well as stochastic preferences. Chari et al. (2007) introduce in their business cycle accounting framework an investment wedge to measure distortions that would occur capital and financial markets. It is like a tax on investment. As the relative price (that we use as observable) maps exactly into this wedge in our artificial economy, we decided to turn to a slightly different measure of capital market distortions as do Kobayashi and Inaba (2006) as well as Cavalcanti et al. (2008).[23] The capital wedge τ_t^k is introduced via the household's period budget constraint

$$... = w_t N_t + (1 - \tau_t^k) r_t u_t K_t.$$

Hence it is like a tax on capital services. This then implies from capital utilization's first order condition that

$$1 - \tau_t^k = \frac{\delta_0}{\alpha} A_t u_t^{1+\nu} K_t / Y_t$$

which allows to compute the empirical wedge from available data of the right hand side variables (rather than using the intertemporal Euler equation). In terms of our original model, the capital wedge equals the inverse of the markup. In a log-linearized world, we have a relation of the artificial wedge $\widehat{\tau}_t^{m,k}$ and marginal costs $\widehat{\phi}_t$ as

$$\widehat{\tau}_t^{m,k} = -\frac{1 - \tau^{m,k}}{\tau^{m,k}} \widehat{\phi}_t.$$

[23] In fact, Kobayashi and Inaba (2006) prove an equivalence of the capital wedge as well as the investment wedge.

In the steady state, $1-\tau^{m,k}$ equals ϕ which, of course, is the inverse of the markup. Given data on the relative price, utilization rates, output and capital constructed using

$$K_{t+1} = \left(1-\delta_0 \frac{u_t^{1+\nu}}{1+\nu}\right) K_t + I_t$$

as well as a parameter calibration, one can compute an empirical series for the capital wedge. We then use the estimated model and the implied series for $\widehat{\tau}_t^{m,k}$ to construct a series of the model-wedge $\tau_t^{m,k}$. The model wedge replicates the overall empirical pattern as well as the depth of the distortions associated with the market of capital. The investment wedge in Figure 7 is computed from the original Chari et al. (2007) formulation, that is the wedge shows up as

$$\frac{1}{1+\widetilde{\tau}_t^x}.$$

From this we construct a series for $1-\tau_t^x \equiv (1+\widetilde{\tau}_t^x)^{-1}$ and report the realizations for τ_t^x in Figure 7. While, by construction, not identical, the two series – $\{\tau_t^k\}$ and $\{\tau_t^x\}$ – are very similar.

8.4 Bianchi and Nicolò (2017)

We briefly set out the methodology that we apply in Section 6. It closely follows Bianchi and Nicolò (2017) and it does not require to know the (analytical solution) of the boundaries of the determinacy region.[24] The parameters of the log-linearized benchmark model are contained in the vector

$$\Theta \equiv [\alpha, \phi, \mu^y, \mu^a, \mu^k, \delta, \nu, \eta, \beta, \gamma, G/Y, \rho_x, \rho_a, \rho_\Delta, \rho_g, \rho_\theta, \sigma_x, \sigma_a, \sigma_\Delta, \sigma_g, \sigma_\theta].$$

The linear rational expectations (LRE) model can be rewritten in the canonical form

$$\Gamma_0(\Theta)s_t = \Gamma_1(\Theta)s_{t-1} + \Psi(\Theta)\varepsilon_t + \Pi(\Theta)\eta_t, \tag{3}$$

[24] Bianchi and Nicolò (2017) show that their characterization of indeterminate equilibria is equivalent to Lubik and Schorfheide (2003).

where

$$s_t = [\widehat{y}_t, \widehat{c}_t, \widehat{i}_t, \widehat{N}_t, \widehat{k}_{t+1}, \widehat{u}_t, \widehat{\phi}_t, E_t(\widehat{y}_{t+1}), E_t(\widehat{c}_{t+1}), E_t(\widehat{\phi}_{t+1}), E_t(\widehat{u}_{t+1}), \widehat{a}_t^g, \widehat{\mu}_t^y, \widehat{\mu}_t^k, \widehat{\mu}_t^x, \widehat{\mu}_t^a, \widehat{\Delta}_t, \widehat{g}_t, \widehat{\theta}_t]'$$

is a vector of endogenous variables, $\varepsilon_t = [\varepsilon_t^x, \varepsilon_t^a, \varepsilon_t^\Delta, \varepsilon_t^g, \varepsilon_t^\theta]'$ is a vector of exogenous shocks, and $\eta_t = [\eta_t^y, \eta_t^c, \eta_t^\phi, \eta_t^u]'$ collects the one-step ahead forecast errors for the expectational variables of the system. Since our model can generate at most one degree of indeterminacy, Bianchi and Nicolò suggest to append the original linear rational expectations model (3) with the autoregressive process

$$\omega_t = \varphi^* \omega_{t-1} + \upsilon_t - \eta_{f,t} \tag{4}$$

where υ_t is the sunspot shock and $\eta_{f,t}$ can be any element of the forecast errors vector η_t. We choose $\eta_{f,t} = \eta_t^y$. The variable φ^* belongs to the interval (-1,1) when the model is determinate or it is outside the unit circle under indeterminacy. Under determinacy the Blanchard-Kahn condition is satisfied and the absolute value of φ^* is inside the unit circle since the number of explosive roots of the original LRE model in (3) already equals the number of expectational variables in the model. Then the autoregressive process ω_t does not affect the solution for the endogenous variables s_t. On the other hand, under indeterminacy the Blanchard-Kahn condition is not satisfied. The system is characterized by one degree of indeterminacy and it is necessary to introduce another explosive root to fulfill the Blanchard-Kahn condition – the absolute value of φ^* falls outside the unit circle. Denoting the newly-defined vector of endogenous variables $\widehat{s}_t \equiv (s_t, \omega_t)'$ and the vector of exogenous shocks $\widehat{\varepsilon}_t \equiv (\varepsilon_t, \upsilon_t)'$, then the system (3) and (4) can be condensed into

$$\widehat{\Gamma}_0 \hat{s}_t = \widehat{\Gamma}_1 \widehat{s}_{t-1} + \widehat{\Psi} \widehat{\varepsilon}_t + \widehat{\Pi} \eta_t,$$

where

$$\widehat{\Gamma}_0 \equiv \begin{bmatrix} \Gamma_0(\Theta) & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}, \ \widehat{\Gamma}_1 \equiv \begin{bmatrix} \Gamma_1(\Theta) & \mathbf{0} \\ \mathbf{0} & \varphi^* \end{bmatrix}$$

and

$$\widehat{\Psi} \equiv \begin{bmatrix} \Psi(\Theta) & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}, \ \widehat{\Pi} \equiv \begin{bmatrix} \Pi_n(\Theta) & \Pi_f(\Theta) \\ \mathbf{0} & -\mathbf{I} \end{bmatrix}.$$

The matrix $\Pi(\Theta)$ in (3) is partitioned as $\Pi(\Theta) = [\Pi_n(\Theta) \quad \Pi_f(\Theta)]$ without loss of generality. Figure 2 shows that the model's (in-)determinacy regions. To start with, the prior probability of determinacy or indeterminacy is set. The prior probability for determinacy, indeterminacy and source is 52:47:1 in percent. All priors are as in benchmark cases with the exception of the prior for the elasticity of the collateral constraint γ which is now beta-distributed, centered at 0.17 with standard deviation 0.1 and we truncate it to be no more than 0.61. Following Bianchi and Nicolò (2017), the determinacy model is estimated by fixing the parameter φ^* to a value smaller than one (e.g. 0.5) in a way that the model is solved only under determinacy while the indeterminacy model is estimated by fixing φ^* greater than one (e.g. 1.5) in a way that the model is solved only under indeterminacy. All parameters that pertain to the solution under indeterminacy are restricted to zero when we estimate the determinacy model. Lastly, we report the estimation results for the two versions of the model. The "Indeterminacy" column shows that using the alternative estimation method has only a very small effect on the paper's main results in regards to parameter estimates.

8.5 Determinacy versus indeterminacy

Table 16 shows, the estimated parameters that arise from applying Bianchi and Nicolò (2017) are essentially equivalent to our previous results (e.g. Table 2) and thus the implications regarding the important role of animal spirits persist.

Table 16: Estimation (Determinacy vs Indeterminacy)

Parameters	Density[mean,std]	Determinacy		Indeterminacy	
		Mean	90% Interval	Mean	90% Interval
ϕ	Beta[0.88,0.01]	0.891	[0.884,0.899]	0.833	[0.831,0.834]
γ	Beta[0.17,0.10]	0.001	[0.000,0.002]	0.322	[0.315,0.329]
ψ_{yg}	Beta[0.5,0.2]	0.997	[0.996,0.998]	0.965	[0.953,0.977]
x	IGam[44,Inf]	10.48	[9.57,11.34]	47.37	[44.24,50.43]
ρ_x	Beta[0.5,0.2]	0.042	[0.031,0.053]	0.025	[0.008,0.042]
ρ_a	Beta[0.5,0.2]	0.083	[0.073,0.092]	0.029	[0.013,0.045]
ρ_Δ	Beta[0.5,0.2]	0.961	[0.955,0.966]	0.984	[0.981,0.988]
ρ_g	Beta[0.5,0.2]	0.935	[0.923,0.946]	0.986	[0.982,0.989]
ρ_θ	Beta[0.5,0.2]	0.982	[0.978,0.985]	0.992	[0.990,0.994]
σ_η	IGam[0.1,Inf]	—	—	0.862	[0.823,0.904]
σ_x	IGam[0.1,Inf]	0.546	[0.520,0.572]	0.690	[0.645,0.733]
σ_a	IGam[0.1,Inf]	0.544	[0.510,0.578]	0.562	[0.525,0.598]
σ_Δ	IGam[0.1,Inf]	0.608	[0.582,0.633]	0.386	[0.364,0.407]
σ_g	IGam[0.1,Inf]	1.106	[1.049,1.166]	0.945	[0.896,0.993]
σ_θ	IGam[0.1,Inf]	0.258	[0.245,0.270]	0.132	[0.121,0.143]
σ_y^{me}	Uniform	0.290	[0.289,0.290]	0.290	[0.289,0.290]
σ_s^{me}	Uniform	27.40	[27.37,27.42]	27.28	[27.10,27.42]
$\rho(\varepsilon^x, \eta^y)$	Uniform	—	—	-0.406	[-0.466,-0.347]
$\rho(\varepsilon^a, \eta^y)$	Uniform	—	—	0.173	[0.112,0.234]
$\rho(\varepsilon^\Delta, \eta^y)$	Uniform	—	—	0.387	[0.336,0.437]
$\rho(\varepsilon^g, \eta^y)$	Uniform	—	—	0.275	[0.225,0.326]
$\rho(\varepsilon^\theta, \eta^y)$	Uniform	—	—	0.151	[0.090,0.212]

Table 17 shows the variance decomposition for the determinacy model with MEI shocks.

Table 17: Unconditional variance decomposition (Determinacy, MEI shock)

Series/shocks	ε_t^x	ε_t^a	ε_t^Δ	ε_t^g	ε_t^{MEI}	$\varepsilon_{y,t}^{me}$	$\varepsilon_{s,t}^{me}$
$\ln(Y_t/Y_{t-1})$	25.93	11.24	16.37	10.60	30.49	5.36	0.00
$\ln(C_t/C_{t-1})$	44.73	2.73	49.00	0.99	2.56	0.00	0.00
$\ln(A_tI_t/A_{t-1}I_{t-1})$	18.65	17.13	5.87	6.08	52.28	0.00	0.00
$\ln(N_t/\overline{N})$	2.57	3.79	7.51	13.40	72.73	0.00	0.00
$\ln(G_t/G_{t-1})$	19.39	3.53	0.00	77.08	0.00	0.00	0.00
$\ln(A_t/A_{t-1})$	0.00	100	0.00	0.00	0.00	0.00	0.00
Credit spread	0.00	0.00	0.00	0.00	93.87	0.00	6.13

8.6 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. Capacity Utilization: Total Industry (TCU), Percent of Capacity, Seasonally Adjusted, Source: Board of Governors of the Federal Reserve System.

19. Commercial and Industrial Loans (all Commercial Banks), Percent change at Annual Rate, Seasonally Adjusted, Source: Board of Governors of the Federal Reserve System.

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

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

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

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

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

25. Per Capita Hours Worked, $N_t = (9)/(11)$.

26. Credit spread = (14) − (16).