

Real Business Cycles, Animal Spirits, and Stock Market Valuation*

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Abstract

This paper develops a real business cycle model with five types of fundamental shocks and one “equity sentiment shock” that captures animal spirits-driven fluctuations. The representative agent’s perception that movements in equity value are partly driven by sentiment turns out to be close to self-fulfilling. I solve for the sequences of shock realizations that allow the model to exactly replicate the observed time paths of U.S. consumption, investment, hours worked, the stock of physical capital, capital’s share of income, and the S&P 500 market value from 1960:Q1 onwards. The model-identified sentiment shock is strongly correlated with survey-based measures of U.S. consumer sentiment. Counterfactual scenarios with the model suggest that the equity sentiment shock has an important influence on the paths of most U.S. macroeconomic variables.

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Nowhere does history indulge in repetitions so often or so uniformly as in Wall Street. When you read contemporary accounts of booms or panics the one thing that strikes you most forcibly is how little either stock speculation or stock speculators today differ from yesterday. The game does not change and neither does human nature.

From the thinly-disguised biography of legendary speculator Jesse Livermore, by E. Lefevère (1923, p. 180).

1 Introduction

Theories about the interaction of sentiment and expectations have long played a role in efforts to account for fluctuations in economic variables. Pigou (1927, p. 73) attributed fluctuations partly to “psychological causes” which lead people to make “errors of undue optimism or undue pessimism in their business forecasts.” Keynes (1936, p. 156) likened the stock market to a “beauty contest” where participants devoted their efforts not to judging the underlying concept of beauty, but instead to “anticipating what average opinion expects the average opinion to be.” More recently, Akerloff and Shiller (2009, p. 1) assert: “We will never really understand important economic events unless we confront the fact that their causes are largely mental in nature.”

This paper develops a real business cycle model that incorporates the flavor of the above ideas. The model has five types of fundamental shocks that influence labor productivity, labor disutility, the marginal efficiency of investment, the cost of adjusting the capital stock, and capital’s share of income. To capture the Keynesian notion of “animal spirits,” I allow for an “equity sentiment shock” that is unconnected to fundamentals.

The representative agent in the model makes use of a sentiment measure to construct a conditional forecast involving future equity value. Due to the self-referential nature of the model, the agent’s perception that movements in equity value are partly driven by sentiment turns out to be close to self-fulfilling. The agent’s subjective forecast errors are close to white noise with near-zero mean, giving no obvious signal that the sentiment-based forecast rule is misspecified.

I solve for the sequences of shock realizations that allow the model to exactly replicate the observed time paths of U.S. consumption, investment, hours worked, the stock of physical capital, capital’s share of income, and the S&P 500 market value from 1960.Q1 through 2017.Q4. I show that the model-identified sentiment shock is strongly correlated with survey-based measures of U.S. consumer sentiment. Counterfactual scenarios with the model suggest that the equity sentiment shock has an important influence on the paths of most U.S. macroeconomic variables.

There are a variety of ways in which animal spirits-type mechanisms can be incorporated into quantitative business cycle models. The original contributions of Benhabib and Farmer (1994) and Farmer and Guo (1994) exploit the indeterminacy of equilibrium (induced by increasing returns to scale in production) to introduce “sunspot shocks” that give rise to

belief-driven fluctuations under rational expectations.¹ In a series of papers, Farmer (2012, 2013, 2015) introduces animal spirits via a “belief function” that governs agent’s expectations about future asset prices, which in turn, influence the level of employment. The belief function serves to pin down a unique rational expectations equilibrium in a framework that is otherwise missing a sufficient number of equilibrium conditions relative to endogenous variables.

Animal spirits can also be introduced by means of “news shocks” that contain noisy signals about future fundamentals. Agents’ expectations and decisions rationally incorporate the noisy signal, but if the news later turns out to be wrong, it will appear as if the resulting fluctuations were not driven by fundamentals.² Benhabib, Wang, and Wen (2015) show that rational sentiment-driven fluctuations can arise in a model without externalities or non-convexities if firms make decisions based on expected demand while households make decisions based on expected income. Milani (2010, 2017) introduces “expectation shocks” in a New Keynesian model that cause the representative agent’s subjective forecasts to deviate from the forecasts implied by an adaptive learning algorithm. Angeletos, Collard, and Dellas (2018) introduce animal spirits by means of “confidence shocks” that arise from an individual household’s belief that their own signal about productivity is unbiased whereas others receive biased signals. The confidence shock acts as wedge between an individual household’s subjective expectation and the fully-rational expectation that would prevail under complete information and common priors. Chahrour and Ulbricht (2017) introduce “expectation wedges” that represent departures from full-information in an environment that is consistent with rational expectations of all agents. In the model developed here, the equity sentiment shock introduces a wedge between the representative agent’s subjective forecast and the “fundamentals-only” forecast that would prevail under fully-rational expectations.

The shock-identification methodology used here shares some similarities with the approach taken by Farmer and Guo (1995) who use a real business cycle model to identify shocks that affect labor demand versus labor supply. The methodology is also conceptually similar to that of Chari, McGrattan, and Kehoe (2007) who develop a quantitative business cycle model with four “wedges” that relate to labor, investment, productivity, and government consumption. Along similar lines, Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2010) employ quarterly data on seven U.S. macroeconomic variables to identify seven types of fundamental shocks in New Keynesian models. The model parameters are estimated using Bayesian methods, but unlike here, the authors do not consider their model’s implications for equity value. As an alternative to estimation, I calibrate the model’s parameters so that the steady state matches the U.S. data in 1970.Q4—a period when U.S. macroeconomic ratios are close to their long-run means. More recently, Christiano, Motto, and Rostagno (2014) consider a fully-rational model with 10 fundamental shocks that is designed to match 12 macroeconomic

¹These original models required very strong (and likely implausible) degrees of increasing returns to scale to generate indeterminacy. But subsequent iterations introduced various mechanisms that could substantially reduce the required degree of increasing returns for indeterminacy. See, for example, Wen (1998) and Guo and Lansing (2007).

²Chahrour and Jurado (2018) provide an overview of this literature and discuss how the effects of pure shifts in beliefs can be distinguished from changes in future fundamentals.

and financial time series. One of these 10 shocks is an “equity shock” that is designed to help match fluctuations in the net worth of entrepreneurs.

2 Model

The framework for the analysis is a classic real business cycle model along the lines of Hansen (1985), but augmented to allow for: (1) growth in output per person, (2) adjustment costs for physical capital, and (3) various additional shocks. The representative agent’s decision problem is to maximize

$$\widehat{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log(c_t) - D \exp(u_t) \frac{h_t^{1+\gamma}}{1+\gamma} \right], \quad (1)$$

subject to the budget constraint

$$c_t + i_t = w_t h_t + r_t k_t, \quad (2)$$

where c_t is consumption, h_t is hours worked, i_t is investment (or saving), w_t is the real wage per hour, r_t is the real rental rate per unit of capital, and k_t is the stock of physical capital, where quantities are measured in per person terms. The parameter $\beta \in (0, 1)$ is the agent’s subjective time discount factor. The symbol \widehat{E}_t represents the agent’s subjective expectation, conditional on information available at time t . Under rational expectations, \widehat{E}_t corresponds to the mathematical expectation operator E_t evaluated using the objective distribution of all shocks, which are assumed known to the rational agent. The disutility of labor is governed by the second term in (1), where $D > 0$, and $\gamma \geq 0$. The elasticity of intertemporal substitution in labor supply is given by $1/\gamma$. As $\gamma \rightarrow \infty$, the model reduces to one with fixed labor supply. Following Hall (1997), I allow for a shock u_t that shifts the intratemporal trade-off between consumption and leisure. The “labor disutility shock” evolves according to the following stationary AR(1) process

$$u_t = \rho_u u_{t-1} + \varepsilon_{u,t}, \quad |\rho_u| < 1, \quad \varepsilon_{u,t} \sim NID(0, \sigma_{\varepsilon,u}^2), \quad (3)$$

where ρ_u governs the shock persistence and $\varepsilon_{u,t}$ is a normally and independently distributed (*NID*) innovation with mean zero and variance $\sigma_{\varepsilon,u}^2$.

Resources devoted to investment augment the stock of physical capital k_t according to the following law of motion

$$k_{t+1} = B \exp(v_t) k_t^{1-\delta_t} i_t^{\delta_t}, \quad B > 0, \quad (4)$$

$$v_t = \rho_v v_{t-1} + \varepsilon_{v,t}, \quad |\rho_v| < 1, \quad \varepsilon_{v,t} \sim NID(0, \sigma_{\varepsilon,v}^2), \quad (5)$$

$$\delta_t = \delta_{t-1}^{\rho_\delta} \bar{\delta}^{1-\rho_\delta} \exp(\varepsilon_{\delta,t}), \quad |\rho_\delta| < 1, \quad \varepsilon_{\delta,t} \sim NID(0, \sigma_{\varepsilon,\delta}^2), \quad (6)$$

with k_0 , v_0 , and δ_0 given. The nonlinear formulation of equation (4) reflects the presence of capital adjustment costs.³ Lansing (2012) shows that the Cobb-Douglas form of equation (4)

³ Abstracting from shocks, the implicit cost of adjusting the capital stock from one period to the next could be computed as $Bk_t[(n_0 + n_1(i_t/k_t - \bar{i}/\bar{k})) - Bk_t(i_t/k_t)^{\delta}]$ where n_0 and n_1 are Taylor series coefficients and \bar{i}/\bar{k} is the steady-state investment-capital ratio.

can be viewed as a log-linearized version of the nonlinear law of motion for capital employed by Jermann (1998).⁴ Following Cassou and Lansing (1997) and Lansing and Markiewicz (2018), I allow for a “capital law multiplier shock” v_t that evolves as a stationary AR(1) process with persistence parameter ρ_v and innovation variance $\sigma_{\varepsilon,v}^2$. The variable δ_t is a “capital law exponent shock” that represents stochastic variation in the elasticity of new capital with respect to new investment. When $\delta_t < 1$, equation (4) implies the presence of time-varying capital adjustment costs. The logarithm of δ_t evolves as a stationary AR(1) process with persistence parameter ρ_δ , innovation variance $\sigma_{\varepsilon,\delta}^2$, and steady state value $\bar{\delta}$. In addition to time-varying adjustment costs, the two capital law shocks can be viewed as capturing shifts in the marginal efficiency of investment, along the lines of Justiniano, Primiceri, and Tambalotti (2010) and/or stochastic variation in the capital depreciation rate, along the lines of Ambler and Paquet (1994), Liu, Waggoner and Zha (2011), and Furlanetto and Seneca (2014). A study by Greenwood, Hercowitz, and Huffman (1988) was the first to consider shocks to the capital law of motion as an important driving force for business cycle fluctuations. More generally, shocks that appear in the capital law of motion can be interpreted as capturing financial frictions that impact the supply of new capital and the price of claims to existing capital.

The representative agent derives income by supplying labor and capital services to identical competitive firms. Firms produce output according to the technology

$$y_t = A k_t^{\alpha_t} [\exp(z_t) h_t]^{1-\alpha_t}, \quad A > 0, \quad (7)$$

$$z_t = z_{t-1} + \mu + \varepsilon_{z,t}, \quad \varepsilon_{z,t} \sim NID(0, \sigma_{\varepsilon,z}^2), \quad (8)$$

$$\alpha_t = \alpha_{t-1}^{\rho_\alpha} \bar{\alpha}^{1-\rho_\alpha} \exp(\varepsilon_{\alpha,t}), \quad |\rho_\alpha| < 1, \quad \varepsilon_{\alpha,t} \sim NID(0, \sigma_{\varepsilon,\alpha}^2), \quad (9)$$

with z_0 and α_0 given. In equation (7), z_t represents a “labor productivity shock” that evolves as a random walk with drift. The drift parameter $\mu > 0$ determines the trend growth rate of output per person in the economy. Stochastic variation in the production function exponent α_t represents a “factor distribution shock,” along the lines of Young (2004), Ríos-Rull and Santaeulàlia-Llopis (2010), Lansing (2015), and Lansing and Markiewicz (2018). The logarithm of α_t evolves as a stationary AR(1) process with persistence parameter ρ_α , innovation variance $\sigma_{\varepsilon,\alpha}^2$, and steady state value $\bar{\alpha}$.

Profit maximization by firms yields the factor prices

$$w_t = (1 - \alpha_t) y_t / h_t, \quad (10)$$

$$r_t = \alpha_t y_t / k_t, \quad (11)$$

which together imply $y_t = w_t h_t + r_t k_t$. From equation (11), we can see that stochastic variation in α_t ($= r_t k_t / y_t$) will allow the model to capture the observed fluctuations in the U.S. capital share of income (Figure 1).

⁴Specifically, $k_{t+1}/k_t = 1 - d + \psi_0 (i_t/k_t)^{\psi_1} \simeq B_0 \left[(i_t/k_t) / (\bar{i}/\bar{k}) \right]^\delta$, where B_0 and δ are Taylor series coefficients. Stochastic variation in the parameters d , ψ_0 , or ψ_1 would imply stochastic variation in the coefficients B_0 and δ .

The first-order conditions with respect to c_t , h_t , and k_{t+1} are given by

$$\lambda_t = 1/c_t, \quad (12)$$

$$D \exp(u_t) h_t^\gamma = \lambda_t w_t, \quad (13)$$

$$\lambda_t i_t / (\delta_t k_{t+1}) = \beta \widehat{E}_t \lambda_{t+1} [r_{t+1} + (1 - \delta_{t+1}) i_{t+1} / (\delta_{t+1} k_{t+1})], \quad (14)$$

where λ_t is the Lagrange multiplier on the budget constraint (2). From equation (13), we see that an increase in $\exp(u_t)$ is isomorphic to a higher distortionary tax on labor income. In deriving equation (14), I first use the capital law of motion (4) to eliminate i_t from the budget constraint. Since k_{t+1} is known at time t , equation (14) can be rewritten as follows

$$\underbrace{i_t / \delta_t}_{p_t} = \widehat{E}_t \{ M_{t+1} [\underbrace{\alpha_{t+1} y_{t+1} - i_{t+1}}_{d_{t+1}} + \underbrace{i_{t+1} / \delta_{t+1}}_{p_{t+1}}] \}, \quad (15)$$

where $M_{t+1} \equiv \beta (c_{t+1}/c_t)^{-1}$ is the stochastic discount factor. The rewritten first-order condition (15) is now in the form of a standard asset pricing equation where $p_t = i_t / \delta_t$ represents the market value of the agent's equity shares in the firm. The equity shares entitle the agent to a perpetual stream of dividends d_{t+1} starting in period $t+1$. As originally noted by Basu (1987), the functional form of the capital law of motion (4) implies a direct link between the market value of equity and firms' investment in physical capital. This feature of the model is consistent with the observed low-frequency comovement between the real S&P 500 stock market index and real business investment in recent decades, as documented by Lansing (2012).

2.1 Fundamental equity value

Defining the equity value-consumption ratio (a stationary variable) as $x_t \equiv p_t / c_t = i_t / (\delta_t c_t)$, the first order condition (15) becomes

$$\begin{aligned} x_t &= \beta \widehat{E}_t \{ \alpha_{t+1} y_{t+1} / c_{t+1} + (1 - \delta_{t+1}) x_{t+1} \} \\ &= \beta \widehat{E}_t \{ \underbrace{\alpha_{t+1} + [1 - \delta_{t+1} (1 - \alpha_{t+1})]}_{\equiv q_{t+1}} x_{t+1} \}, \end{aligned} \quad (16)$$

where I have used the budget constraint (2) at time $t+1$ and the definition of x_{t+1} to make the substitution $y_{t+1}/c_{t+1} = 1 + \delta_{t+1} x_{t+1}$. At this point, it is convenient to define a nonlinear change of variables such that q_{t+1} represents the composite stationary variable that the agent must forecast.⁵ The agent's first-order condition (16) becomes $x_t = \beta \widehat{E}_t q_{t+1}$. Now using the definition of q_t to make the substitution $x_t = (q_t - \alpha_t) / [1 - \delta_t (1 - \alpha_t)]$ yields the following transformed version of the agent's first order condition

$$q_t = \alpha_t + \beta [1 - \delta_t (1 - \alpha_t)] \widehat{E}_t q_{t+1}. \quad (17)$$

⁵This nonlinear change of variables technique is also employed by Lansing (2010, 2016).

The fundamental equity value is obtained by solving equation (17) under the assumption of rational expectations such that $\widehat{E}_t q_{t+1} = E_t q_{t+1}$. As shown in Appendix A, a log-linear approximate version of the fundamental solution is given by

$$q_t^f = \bar{q}^f \left[\frac{\alpha_t}{\bar{\alpha}} \right]^{\gamma_\alpha} \left[\frac{\delta_t}{\bar{\delta}} \right]^{\gamma_\delta}, \quad (18)$$

where $\bar{q}^f \equiv \exp[E \log(q_t^f)]$ and γ_α and γ_δ are solution coefficients that depend on model parameters. Given the value of q_t^f , we can recover the fundamental equity value-consumption ratio as

$$x_t^f \equiv \frac{p_t^f}{c_t} = \frac{q_t^f - \alpha_t}{1 - \delta_t(1 - \alpha_t)}, \quad (19)$$

which shows that p_t^f/c_t will only move in response to the two fundamental shocks α_t and δ_t .

2.2 Introducing animal spirits

Numerous empirical studies starting with Shiller (1981) and LeRoy and Porter (1981) have shown that stock prices appear to exhibit excess volatility when compared to fundamentals, as measured by the discounted stream of ex post realized dividends.⁶ To capture the notion of animal spirits-driven excess volatility, I allow for an “equity sentiment shock” that is unconnected to fundamentals. I postulate that the representative agent’s perceived law of motion (PLM) for the composite variable q_t in equation (17) takes into account the possibility of departures from the fundamental value q_t^f . Specifically, the agent’s PLM takes the form

$$q_t = q_t^f \exp(s_t), \quad (20)$$

$$s_t = \rho_s s_{t-1} + \varepsilon_{s,t}, \quad |\rho_s| < 1, \quad \varepsilon_{s,t} \sim NID(0, \sigma_{\varepsilon,s}^2), \quad (21)$$

where the sentiment shock s_t evolves as a stationary AR(1) process with persistence parameter ρ_s , innovation variance $\sigma_{\varepsilon,s}^2$, and a steady state value of zero. The agent can learn the parameters that govern the sentiment shock by constructing the time series $\log(q_t/q_t^f)$ where q_t is the actual value observed in the data and q_t^f is the value predicted by fundamentals from equation (18).

Given the PLM (20), the agent’s subjective forecast can be computed as follows

$$\begin{aligned} \widehat{E}_t q_{t+1} &= \widehat{E}_t q_{t+1}^f \exp(\rho_s s_t + \frac{1}{2} \sigma_{\varepsilon,s}^2), \\ &= \bar{q}^f \exp(\frac{1}{2} \gamma_\alpha^2 \sigma_{\varepsilon,\alpha}^2 + \frac{1}{2} \gamma_\delta^2 \sigma_{\varepsilon,\delta}^2 + \frac{1}{2} \sigma_{\varepsilon,s}^2) \left[\frac{\alpha_t}{\bar{\alpha}} \right]^{\rho_\alpha \gamma_\alpha} \left[\frac{\delta_t}{\bar{\delta}} \right]^{\rho_\delta \gamma_\delta} \exp(\rho_s s_t), \end{aligned} \quad (22)$$

where $\widehat{E}_t q_{t+1}^f (= E_t q_{t+1}^f)$ is the “fundamentals-only” forecast that ignores the sentiment shock. Equation (22) is qualitatively consistent with the findings of Frydman and Stillwagon (2018). Using survey data of investors’ expectations about future stock returns, they present evidence that expectations are jointly driven by fundamental factors and extrapolation. Substituting

⁶Lansing and LeRoy (2014) provide a recent update on this literature.

the agent's subjective forecast (22) into the first order condition (17) yields the actual law of motion (ALM) for q_t . Due to the self-referential nature of the model whereby q_t depends in part on $\widehat{E}_t q_{t+1}$, the resulting ALM for q_t does indeed depend on s_t , making the agent's beliefs close to self-fulfilling. Given the ALM for q_t , we can recover the resulting equity value-consumption ratio as

$$x_t \equiv \frac{p_t}{c_t} = \frac{q_t - \alpha_t}{1 - \delta_t(1 - \alpha_t)} = \beta \widehat{E}_t q_{t+1}, \quad (23)$$

where $q_t = q(\alpha_t, \delta_t, s_t)$. Hence, p_t/c_t will move in response to movements in α_t , δ_t , or s_t .

Given the value of x_t from equation (23), we can compute the values of the other macroeconomic variables using the following equations

$$h_t = [(1 - \alpha_t)(1 + \delta_t x_t) D^{-1} \exp(-u_t)]^{\frac{1}{1+\gamma}}, \quad (24)$$

$$y_t = A k_t^{\alpha_t} [\exp(z_t) h_t]^{1-\alpha_t}, \quad (25)$$

$$c_t = y_t / (1 + \delta_t x_t), \quad (26)$$

$$i_t = y_t \delta_t x_t / (1 + \delta_t x_t), \quad (27)$$

where I have used the budget relationship $y_t/c_t = 1 + \delta_t x_t$.

3 Parameter values and shocks

Figure 1 plots the U.S. data versions of the model variables y_t , c_t , i_t , h_t , k_t , p_t , and α_t . Figure 2 plots the U.S. data versions of the model ratios c_t/y_t , i_t/y_t , k_t/y_t , and p_t/y_t .⁷ From Figure 2, we see that the U.S. macroeconomic ratios are all close to their long-run means in 1970.Q4. I choose parameters so that the steady-state, trend, or ergodic mean values of the model variables correspond to the values observed in the data in 1970.Q4.⁸ Given a time endowment normalized to one, a steady state target of $h_t = 0.3$ implies that the representative agent spends about one-third of available time in market work. Table 1 summarizes the parameter values.

Table 1: Model Parameter Values

| Parameter | Value | Description/Target |
|----------------|--------|---|
| $\bar{\alpha}$ | 0.3507 | $\alpha_t = \bar{\alpha}$ in 1970.Q4. |
| A | 0.9662 | $z_t = 0$ and $k_t/y_t = 10.248$ in 1970.Q4. |
| $\bar{\delta}$ | 0.0639 | $\delta_t = \bar{\delta}$ and $i_t/y_t = 0.2690$ in 1970.Q4. |
| B | 1.2894 | $v_t = 0$ and $k_{t+1}/k_t = B (i_t/k_t)^{\bar{\delta}} = 1.0219$ in 1970.Q4. |
| D | 2.9610 | $u_t = 0$ and $h_t = 0.3$ in 1970.Q4. |
| β | 0.9801 | $s_t = 0$ and $p_t/y_t = 4.2112$ in 1970.Q4. |
| γ | 0 | Indivisible labor: Rogerson (1988), Hansen (1985). |

⁷The sources and methods used to construct the U.S. data versions of the model variables are described in Appendix B.

⁸As shown in Appendix A, the ergodic mean value of $\bar{q}^f \equiv \exp[E \log(q_t^f)]$ depends on the shock variances $\sigma_{\varepsilon, \delta}^2$ and $\sigma_{\varepsilon, \alpha}^2$. Given the shock variances, the value of the discount factor β is chosen such that $\bar{q}^f = q_t$ in 1970.Q4.

Given the parameter values in Table 1, I solve for the sequences of stochastic shocks that allow the calibrated model to exactly replicate the observed time paths of the seven U.S. macro variables plotted in Figure 1. Of the seven variables, only six are independent since $y_t = c_t + i_t$. The model has six independent shocks, so each shock series is uniquely identified.⁹ The model shocks are: z_t (labor productivity), u_t (labor disutility), v_t (capital law multiplier), δ_t (capital law exponent), α_t (factor distribution), and s_t (equity sentiment). The time series for α_t is directly pinned down by U.S. data on capital's share of income. The time series for the remaining five shocks are computed using the following equations:

$$z_t = [\log(y_t) - \log(Ak_t^{\alpha_t}h_t^{1-\alpha_t})] / (1 - \alpha_t), \quad (28)$$

$$\delta_t = (i_t/y_t) / [(p_t/c_t)(1 - i_t/y_t)], \quad (29)$$

$$v_t = \log(k_{t+1}/k_t) - \log(B) - \delta_t \log(i_t/k_t), \quad (30)$$

$$u_t = \log \left\{ (1 - \alpha_t)(c_t/y_t)^{-1} / (Dh_t^{1+\gamma}) \right\} \quad (31)$$

$$s_t = (1/\rho_s) \log \left\{ (p_t/c_t) (\beta \widehat{E}_t q_{t+1}^f)^{-1} \exp(-\frac{1}{2}\sigma_{\varepsilon,s}^2) \right\}, \quad (32)$$

where the right-side macroeconomic variables take on the values observed in the U.S. data from 1960.Q1 to 2017.Q4.¹⁰ If a shock appears on the right side, then it takes on the value identified in a previous equation. In the case of equation (32), the fundamentals-only forecast $\widehat{E}_t q_{t+1}^f (= E_t q_{t+1}^f)$ is computed using the fundamental solution (18). The parameters β , ρ_s and $\sigma_{\varepsilon,s}$ influence computed time series for s_t . I start with initial guesses for these parameters and then iterate until convergence.

The six identified shock series are plotted in Figure 3. By construction, all shocks are equal to their trend or steady state values in 1970.Q4.¹¹ The labor productivity shock z_t drops sharply in the aftermath of the Great Recession and has yet to fully recover. The labor disutility shock u_t trends down over time, allowing the model to match the observed time path of h_t in the data, despite the sustained weakness in labor productivity (and the real wage) together with the decline in labor's share of income implied by the increase in α_t .¹² The capital law multiplier shock v_t is almost perfectly negatively correlated with the quantity $1 - \delta_t$, representing the exponent on k_t in the capital law of motion (4). This offsetting pattern allows the model to match the smooth time path of k_t in the data while simultaneously matching the more-volatile time paths of i_t and p_t . Finally, the equity sentiment shock s_t mimics movements the U.S. valuation ratio p_t/y_t shown earlier in Figure 2. The sentiment shock reaches its maximum value in 2000.Q1, coinciding with the peak of the NASDAQ technology stock bubble. Empirical valuation models similarly imply that U.S. equity values were above levels that can be justified by fundamentals around this time (Lansing 2017). The sentiment

⁹Lansing and Markiewicz (2018) and Gelain, Lansing, and Natvik (2018) undertake similar shock identification exercises, but in the context of different models.

¹⁰Since the computation of v_t requires data at time $t+1$, I set the end-of-sample shock value to $v_T = \rho_v v_{T-1}$.

¹¹The trend value of z_t is constructed as $\bar{z}_t = \bar{z}_{t-1} + \mu$, where μ is the sample mean of Δz_t and $\bar{z}_t = z_t$ in 1970.Q4.

¹²Kaplan and Schulhofer-Wohl (2018) show that labor disutility, as measured by "feelings about work" from surveys, has shifted in significant ways since 1950.

shock is negative from 1973.Q4 through 1997.Q1 and from 2002.Q2 through 2017.Q4. These two intervals include five out of the eight U.S. recessions that have occurred since 1960.

Table 2 shows the values of the shock parameters implied by the identification exercise. The five stationary shocks all exhibit very strong persistence—close to a unit root. In this way, variables which are presumed stationary in the model (e.g., hours worked per person, capital’s share of income, and the equity value-consumption ratio) can be made to replicate the sustained uptrends or downtrends observed in the U.S. data.

Table 2: Model-Identified Shock Parameters

| Shock | Values | |
|----------------------------------|------------------------|--|
| Labor productivity, z_t | $\mu = 0.0046$ | $\sigma_{\varepsilon,z} = 0.0301$ |
| Labor disutility, u_t | $\rho_u = 0.9945$ | $\sigma_{\varepsilon,u} = 0.0099$ |
| Capital law multiplier, v_t | $\rho_v = 0.9732$ | $\sigma_{\varepsilon,v} = 0.0273$ |
| Capital law exponent, δ_t | $\rho_\delta = 0.9789$ | $\sigma_{\varepsilon,\delta} = 0.0820$ |
| Factor distribution, α_t | $\rho_\alpha = 0.9796$ | $\sigma_{\varepsilon,\alpha} = 0.0130$ |
| Equity sentiment, s_t | $\rho_s = 0.9760$ | $\sigma_{\varepsilon,s} = 0.0423$ |

4 Quantitative Analysis

4.1 Model-identified sentiment shock

Movements in the equity sentiment shock capture the notion of animal spirits-driven fluctuations. Figure 4 plots impulse response functions for a one standard deviation innovation of the equity sentiment shock. The panels show the percent deviation of each variable from its no-shock trend. On impact, output, hours worked, investment, and equity value all increase. But since the capital stock cannot respond immediately, the initial increase in output is not sufficient to allow both consumption and investment to increase on impact. Consumption drops slightly on impact, but then increases with the other variables as the capital stock starts increasing in response to higher investment. Since δ_t is constant here, movements in equity value ($p_t = i_t/\delta_t$) exactly mimic the movements in investment.

Figure 5 provides a check on the reasonableness of the model sentiment shock. The identified series for s_t is plotted together with the University of Michigan’s consumer sentiment index and the Conference Board’s consumer confidence index. Each series is demeaned and normalized by its standard deviation. The model equity sentiment shock is strongly correlated with both of the survey-based measures of U.S. consumer sentiment. The correlation coefficient between s_t and the University of Michigan index is 0.63. The correlation coefficient between s_t and the Conference Board index is 0.71. The strong correlation is perhaps not surprising because the identified series for s_t helps the model to exactly replicate the time path of U.S. equity value. There is a well-documented link between equity price (or equity return) movements in the data and measures of investor or consumer sentiment.¹³ Still, Figure 5 confirms that it is appropriate to view the model-identified series for s_t as capturing a

¹³See, for example, Fisher and Statman (2003), Brown and Cliff (2004, 2005), Schmeling (2009), Greenwood and Shleifer (2014), Frydman and Stillwagon (2018), and Lansing, LeRoy, and Ma (2018).

measure of sentiment.

4.2 Representative agent’s forecast errors

Recall from Section 2.2 that the equity sentiment shock introduces a wedge between the agent’s subjective forecast $\widehat{E}_t q_{t+1}$ and the “fundamentals-only” forecast that ignores the sentiment shock. Table 3 summarizes the properties of the agent’s percentage forecast errors, measured as $err_{t+1} = 100(q_{t+1} - \widehat{E}_t q_{t+1})/q_{t+1}$. The forecast errors are computed for the sample period 1960.Q2 to 2017.Q4 using the model together with the six identified shock series shown in Figure 3. The agent’s perception that movements in q_t are partly driven by movements in s_t turns out to be close to self-fulfilling. Table 3 shows that the agent’s subjective forecast errors are close to white noise with near-zero mean, giving no obvious signal that the agent’s sentiment-based forecast rule (22) is misspecified. In contrast, the fundamentals-only forecast performs very poorly when the ALM is given by $q_t = q(\alpha_t, \delta_t, s_t)$. Put another way, the typical agent’s use of the sentiment-based forecast rule serves to shift the moments of the forecast variable q_{t+1} so that any individual agent would perceive no accuracy gain from switching to the fundamentals-only forecast.¹⁴ The first-order condition (16) can also be written as $x_t = \beta \widehat{E}_t q_{t+1}$, where $x_t \equiv p_t/c_t$. Consequently, very similar results are obtained if the agent’s percentage forecast errors are instead measured as $err_{t+1} = 100(x_{t+1} - \widehat{E}_t x_{t+1})/x_{t+1}$.

Table 3. Properties of Representative Agent’s Forecast Errors

| Statistic | Subjective forecast | Fundamentals-only forecast |
|------------------------------|---------------------|----------------------------|
| $E(err_{t+1})$ | 0.63% | -15.9% |
| $\sqrt{E[(err_{t+1})^2]}$ | 0.84% | 2.62% |
| $Corr(err_{t+1}, err_t)$ | 0.12 | 0.87 |
| $Corr(err_{t+1}, err_{t-1})$ | -0.02 | 0.83 |
| $Corr(err_{t+1}, err_{t-2})$ | 0.02 | 0.81 |

Note: Forecast errors are computed for the sample period 1960.Q2 to 2017.Q4 using the model together with the six identified shock series shown in Figure 3.

4.3 Counterfactual scenarios

Figure 6 displays counterfactual scenarios for three model variables: y_t , h_t , and p_t . In each set of panels from top to bottom, I turn off one or more shocks (as indicated) while leaving the other shocks in place. The purpose of the exercise is see which shocks are the most important for allowing a given model variable to fit the data. A large gap between the counterfactual path and the U.S. data path (solid blue line) implies that the omitted shock(s) play an important role in allowing the model variable to match the path of the corresponding U.S. variable.

In the top set of panels, I shut off the labor productivity shock innovation $\varepsilon_{z,t}$ (dashed red lines) and then shutoff the labor disutility shock u_t (dotted green lines). The labor productivity shock serves to hold down the levels of y_t and p_t , particularly near the end of the data sample. But this shock has no impact on h_t because it operates only through the ratio c_t/y_t , which is

¹⁴Lansing (2006) obtains a similar result in a asset pricing model where the typical agent employs extrapolative expectations.

neutral to such a shock in the case of logarithmic utility. The labor disutility shock serves to push up y_t and h_t by a significant amount, while also pushing up p_t in a more modest way.

In the middle set of panels, I shut off the two capital law of motion shocks v_t and δ_t (dashed red lines) and then shutoff the factor distribution shock α_t (dotted green lines). The two capital law shocks serve to hold down the end-of-sample level of y_t , but have only small effects on the end-of-sample levels of h_t and p_t . The factor distribution shock serves to push up the levels y_t and p_t , particularly near the end of the data sample when α_t is rising more rapidly. As expected, the net effect of a rising capital income share is to push down the level of h_t . The model implication that movements in α_t can have an important impact on the level of p_t is consistent with a recent empirical study by Greenwald, Lettau, and Ludvigson (2014) who find that highly persistent “factor share shocks” are an important driver of U.S. stock prices over the period 1952 to 2012.¹⁵

In the bottom set of panels, I shut off the equity sentiment shock s_t (dashed red lines) and then show the paths implied by a deterministic version of the model (dotted green lines). By itself, the equity sentiment shock serves to mostly hold down the levels of y_t , h_t , and p_t , except around the year 2000, coinciding with the peak of the NASDAQ technology stock bubble.

To quantify the relative importance of the various shocks for each macro variable, I compute the mean absolute gaps (measured in percent) between the counterfactual path and the U.S. data path. The results are shown in Table 3. By this metric, the labor disutility shock is the most important shock for h_t . The capital law of motion shocks are most important shocks for c_t and k_t . The equity sentiment shock is the most important shock for y_t , i_t , and p_t . The last column shows the average of the mean absolute gaps across the six macroeconomic variables. By this metric, the equity sentiment shock has the strongest overall influence on the paths of the six macroeconomic variables. This result is remarkably similar to the findings of Angeletos, Collard, and Dellas (2018) who state “the confidence shock emerges as the main driver of the business cycle within medium-scale DSGE models that contain multiple other shocks.”

Table 3: Mean Absolute Gaps: Model versus Data

| Scenario | y_t | c_t | i_t | h_t | k_t | p_t | Ave. |
|------------------------------|-------|-------|-------|-------|-------|-------|------|
| Baseline simulation | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| No labor productivity shock | 9.88 | 9.88 | 9.88 | 0 | 6.30 | 9.88 | 7.63 |
| No labor disutility shock | 11.7 | 11.7 | 11.7 | 12.4 | 10.7 | 11.7 | 11.7 |
| No capital law shocks | 12.2 | 13.7 | 19.8 | 4.31 | 37.7 | 28.5 | 19.4 |
| No factor distribution shock | 13.46 | 11.9 | 17.8 | 2.76 | 15.0 | 17.8 | 13.1 |
| No equity sentiment shock | 13.48 | 7.58 | 31.2 | 6.28 | 28.4 | 31.2 | 19.7 |
| Deterministic model | 10.9 | 12.0 | 9.96 | 9.60 | 26.8 | 40.6 | 18.3 |

Notes: Each number is the mean absolute gap (measured in percent) between the path of the model variable under a given scenario and the path of the corresponding variable in U.S. data from 1960.Q1 to 2017.Q4. Boxed entries indicate the largest percentage gaps for each variable when other shocks are present.

¹⁵Lansing (2015) shows that the introduction of “distribution shocks” can substantially magnify the mean equity premium in a production economy with capital owners and workers.

5 Conclusion

The main contribution of this paper is to show that an “equity sentiment shock” can be an important element in allowing a standard real business cycle model to exactly replicate the evolution of U.S. macroeconomic variables and the S&P 500 market value from 1960.Q1 through 2017.Q4. The model-identified sentiment shock is highly correlated with survey-based measures of U.S. consumer sentiment, validating its interpretation as a type of “animal spirits,” along the lines envisioned by Pigou (1927) and Keynes (1936).

In the model, the representative agent makes use of a sentiment measure to construct a conditional forecast involving future equity value. Due to the self-referential nature of the model, the agent’s belief that movements in equity value are partly driven by sentiment turns out to be close to self-fulfilling. From the perspective of an individual agent, switching to a fundamentals-only forecast would appear to reduce forecast accuracy, so there is no incentive to switch.

A Appendix: Fundamental solution

This appendix provides the details regarding the fundamental solution q_t^f shown in equation (18). First imposing rational expectations and then log linearizing the right-side of the transformed first order condition (17) yields

$$q_t^f = b_0 \left[\frac{\alpha_t}{\bar{\alpha}} \right]^{b_1} \left[\frac{\delta_t}{\bar{\delta}} \right]^{b_2} E_t \left[\frac{q_{t+1}^f}{\bar{q}^f} \right]^{b_3}, \quad (\text{A.1})$$

where b_0 , b_1 , b_2 , and b_3 are Taylor-series coefficients. The expressions for the Taylor-series coefficients are

$$b_0 = \bar{\alpha} + \beta [1 - \bar{\delta} (1 - \bar{\alpha})] \bar{q}^f, \quad (\text{A.2})$$

$$b_1 = \frac{\bar{\alpha} (1 + \beta \bar{\delta} \bar{q}^f)}{\bar{\alpha} + \beta [1 - \bar{\delta} (1 - \bar{\alpha})] \bar{q}^f}, \quad (\text{A.3})$$

$$b_2 = \frac{-\beta \bar{\delta} (1 - \bar{\alpha}) \bar{q}^f}{\bar{\alpha} + \beta [1 - \bar{\delta} (1 - \bar{\alpha})] \bar{q}^f}, \quad (\text{A.4})$$

$$b_3 = \frac{\beta [1 - \bar{\delta} (1 - \bar{\alpha})] \bar{q}^f}{\bar{\alpha} + \beta [1 - \bar{\delta} (1 - \bar{\alpha})] \bar{q}^f} \quad (\text{A.5})$$

where the approximation points are $\bar{\alpha} = \exp[E \log(\alpha_t)]$, $\bar{\delta} = \exp[E \log(\delta_t)]$ and $\bar{q}^f \equiv \exp[E \log(q_t^f)]$.

A conjecture for the fundamental solution takes the form $q_t^f = \bar{q}^f [\alpha_t / \bar{\alpha}]^{\gamma_\alpha} [\delta_t / \bar{\delta}]^{\gamma_\delta}$. The conjectured solution is iterated ahead one period and then substituted into the right-side of equation (A.1) together with the laws of motion for α_{t+1} and δ_{t+1} from equations (9) and (6), respectively. After evaluating the conditional expectation and then collecting terms, we have

$$q_t^f = \underbrace{b_0 \exp \left[\frac{1}{2} (\gamma_\alpha b_3)^2 \sigma_{\varepsilon, \alpha}^2 + \frac{1}{2} (\gamma_\delta b_3)^2 \sigma_{\varepsilon, \delta}^2 \right]}_{=\bar{q}^f} \times \left[\frac{\alpha_t}{\bar{\alpha}} \right]^{\underbrace{b_1 + \rho_\alpha \gamma_\alpha b_3}_{\gamma_\alpha}} \times \left[\frac{\delta_t}{\bar{\delta}} \right]^{\underbrace{b_2 + \rho_\delta \gamma_\delta b_3}_{=\gamma_\delta}} \quad (\text{A.6})$$

which yields three equations in the three unknown solution coefficients \bar{q}^f , and γ_α and γ_δ . For the baseline calibration, we have $\bar{q}^f = 5.868$, $\gamma_\alpha = 1.034$ and $\gamma_\delta = -0.499$. An increase in capital's share of income α_t will cause q_t^f to increase. An increase in the capital law of motion exponent δ_t will cause q_t^f to decrease. It can be shown that for the baseline calibration, the fundamental equity value-consumption ratio $x_t^f \equiv p_t^f / c_t$ computed from equation (19) will move in the same direction as q_t^f .

B Appendix: Data sources and methods

I start with data on nominal personal consumption expenditures on nondurable goods *plus* services (C_t), nominal private nonresidential fixed investment *plus* nominal personal consumption expenditures on durable goods (I_t), the corresponding price indices for each of the various

nominal expenditure series that sum to C_t and I_t , and U.S. population. All of this data are from the Federal Reserve Bank of St. Louis' FRED database. I define the nominal ratios C_t/Y_t and I_t/Y_t , where $Y_t \equiv C_t + I_t$. The nominal ratios capture shifts in relative prices. I then deflate Y_t by an output price index constructed as the weighted-average of the price indices for the various nominal expenditure series that sum to C_t and I_t , where the weights are the nominal expenditure ratios relative to Y_t . The level of real output per person y_t in the data is normalized to 1.0 in 1970.Q4. The real per person series c_t and i_t are constructed by applying the nominal ratios C_t/Y_t and I_t/Y_t to the deflated output series and then dividing by U.S. population. In this way, the real per person series reflect the same resource allocation ratios as the nominal per person series.

Data for h_t are hours worked of all persons in the nonfarm business sector from FRED, divided by U.S. population and then normalized to equal 0.3 in 1970.Q4.

The data for k_t are constructed using the historical-cost net stock of private nonresidential fixed assets plus the historical-cost net stock of consumer durable goods, both in billions of dollars at year end, from the Bureau of Economic Analysis (BEA), NIPA Table 4.3, line 1 and Table 8.3, line 1, respectively. The data are only available at annual frequency, so I first create a quarterly series by log-linear interpolation. The nominal capital stock series is deflated using the output price index mentioned above and then divided by U.S. population. I normalize the real per person series for k_t to deliver a target value of $i_t/k_t = 0.0263$ in 1970.Q4. The target value is arbitrary given that the model parameters B and $\bar{\delta}$ can be adjusted to hit any desired target value. I choose the target value of i_t/k_t to coincide with the steady state value implied by a model with no capital adjustment costs, such that $i_t/k_t = k_{t+1}/k_t - 1 + d$, where $d = 0.02$ is a typical quarterly depreciation rate for physical capital. For the normalization, I employ the mean quarterly growth rate of the real per person series which implies $k_{t+1}/k_t = \exp(0.0062)$ in steady state. I calibrate the value of A in the production function (7) to yield $y_t = 1$ in 1970.Q4 when k_t is equal to the normalized capital stock in 1970.Q4. This procedure delivers a sample mean of $k_t/y_t = 9.80$ from 1960.Q1 to 2017.Q4.

Following Lansing (2015) and Lansing and Markiewicz (2018), capital's share of income is measured as 1 minus the ratio of employee compensation to gross value added of the corporate business sector. Both series are from the BEA, NIPA Table 1.14, lines 1 and 4.

To construct data for p_t , I start with the nominal market capitalization of the S&P 500 stock market index from www.siblisresearch.com. The nominal market capitalization is deflated using the output price index noted above and then divided by U.S. population to create a series for real equity value per person.

The University of Michigan consumer sentiment index is from www.sca.isr.umich.edu/tables.html. The Conference Board's consumer confidence index is from www.conference-board.org/data.

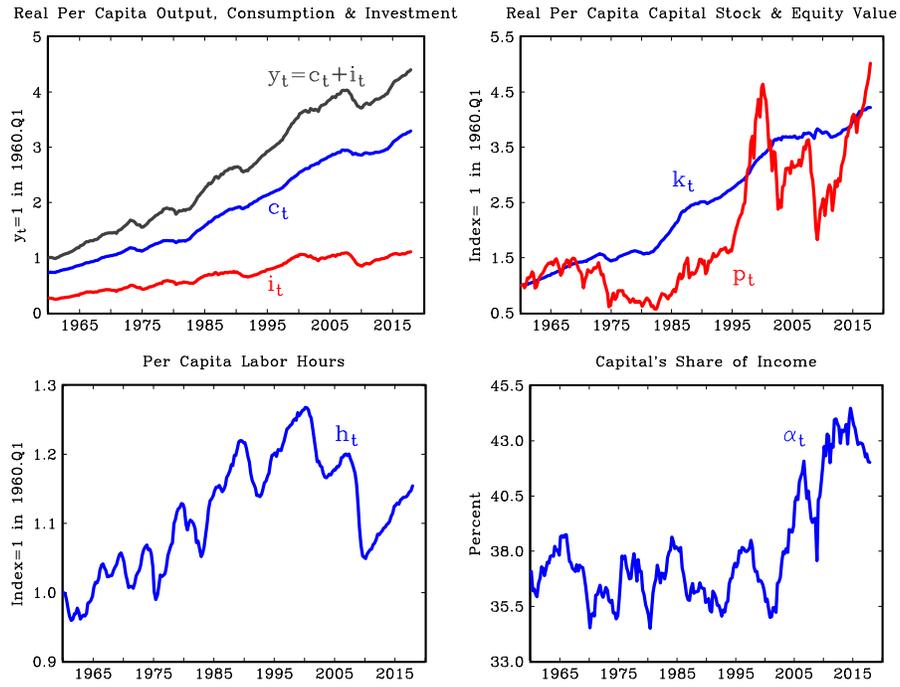
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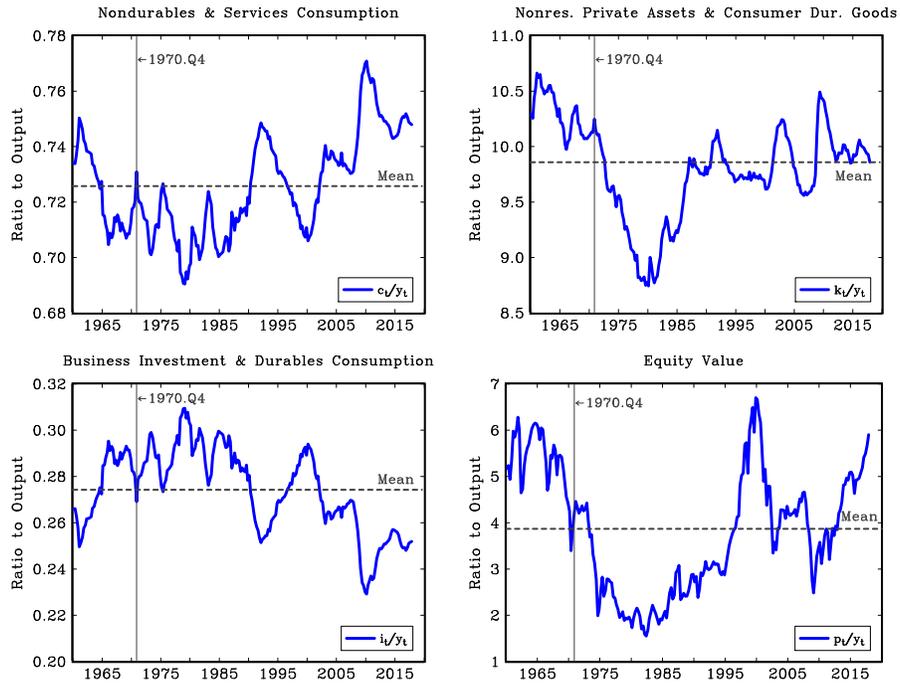
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Figure 1: *U.S. Macroeconomic Variables*



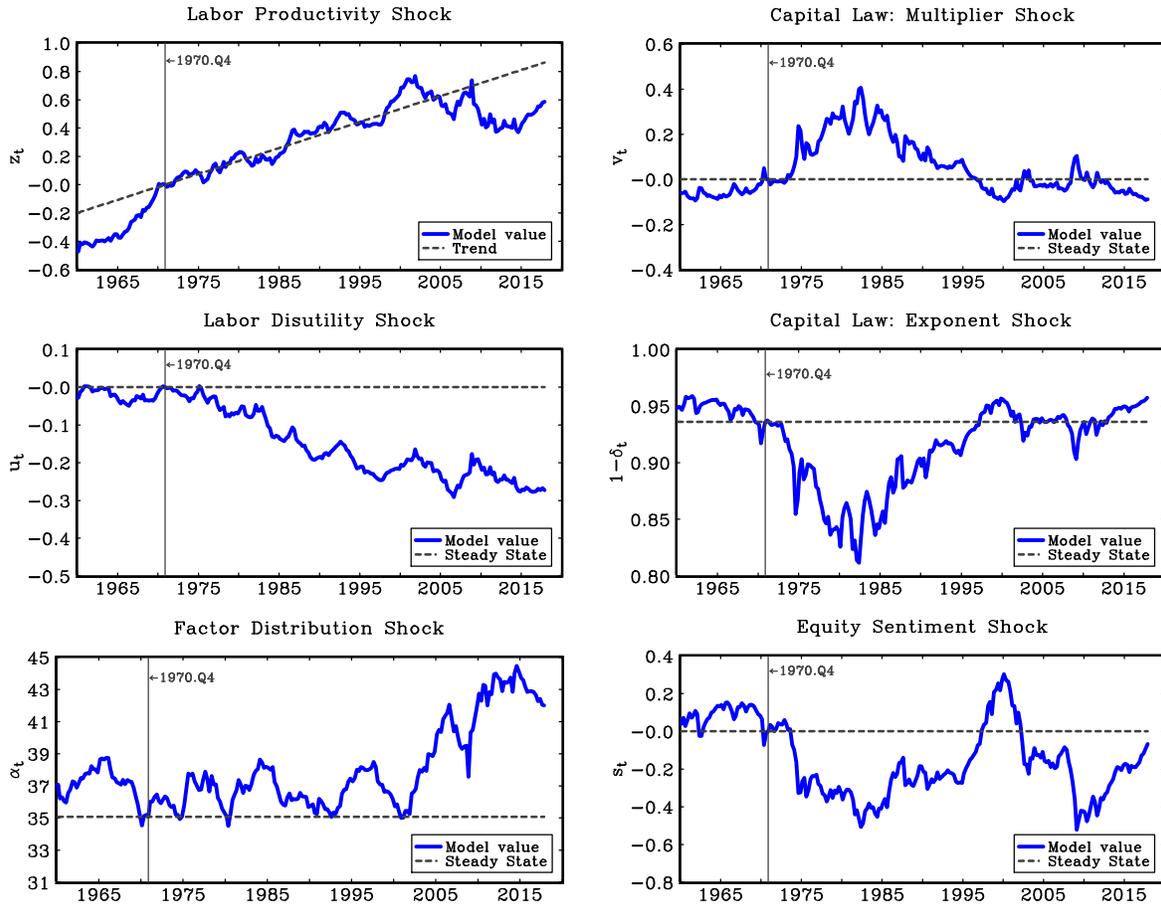
The baseline simulation exactly replicates the observed U.S. time paths of the variables y_t , c_t , i_t , h_t , k_t , p_t , and α_t from 1960.Q1 to 2017.Q4. Data series are constructed as described in Appendix B.

Figure 2: *U.S. Macroeconomic Ratios*



The ratios of U.S. macroeconomic variables to output are close to their long-run means in 1970.Q4. Parameter values are chosen so that the steady-state, trend, or ergodic mean values of model variables correspond to the values observed in the data in 1970.Q4.

Figure 3: *Model-Identified Shocks*



The panels show the time series of stochastic shocks that are needed for the model to exactly replicate the time paths of the seven U.S. macroeconomic variables shown earlier in Figure 1. By construction, all shocks are equal to their trend or steady state values in 1970.Q4. The equity sentiment shock reaches its maximum value in 2000.Q1, coinciding with the peak of the NASDAQ technology stock bubble.

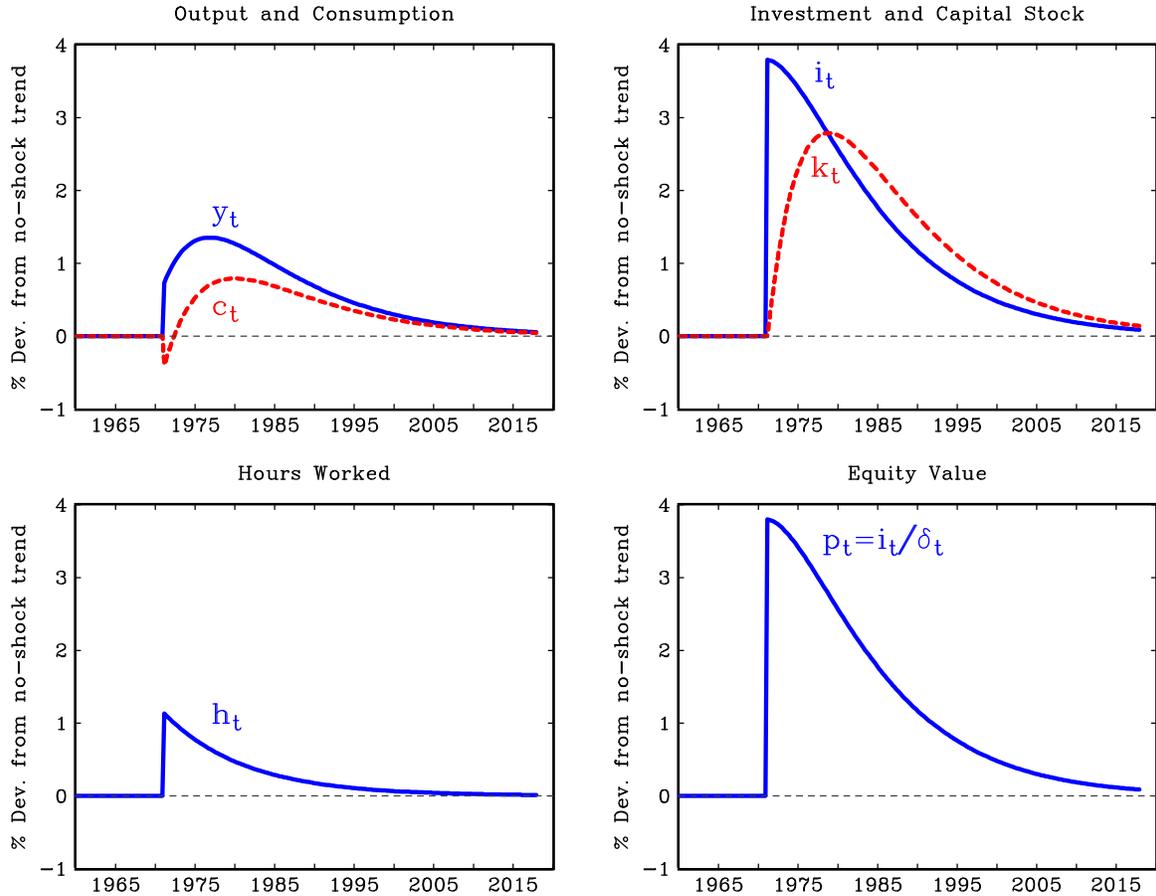
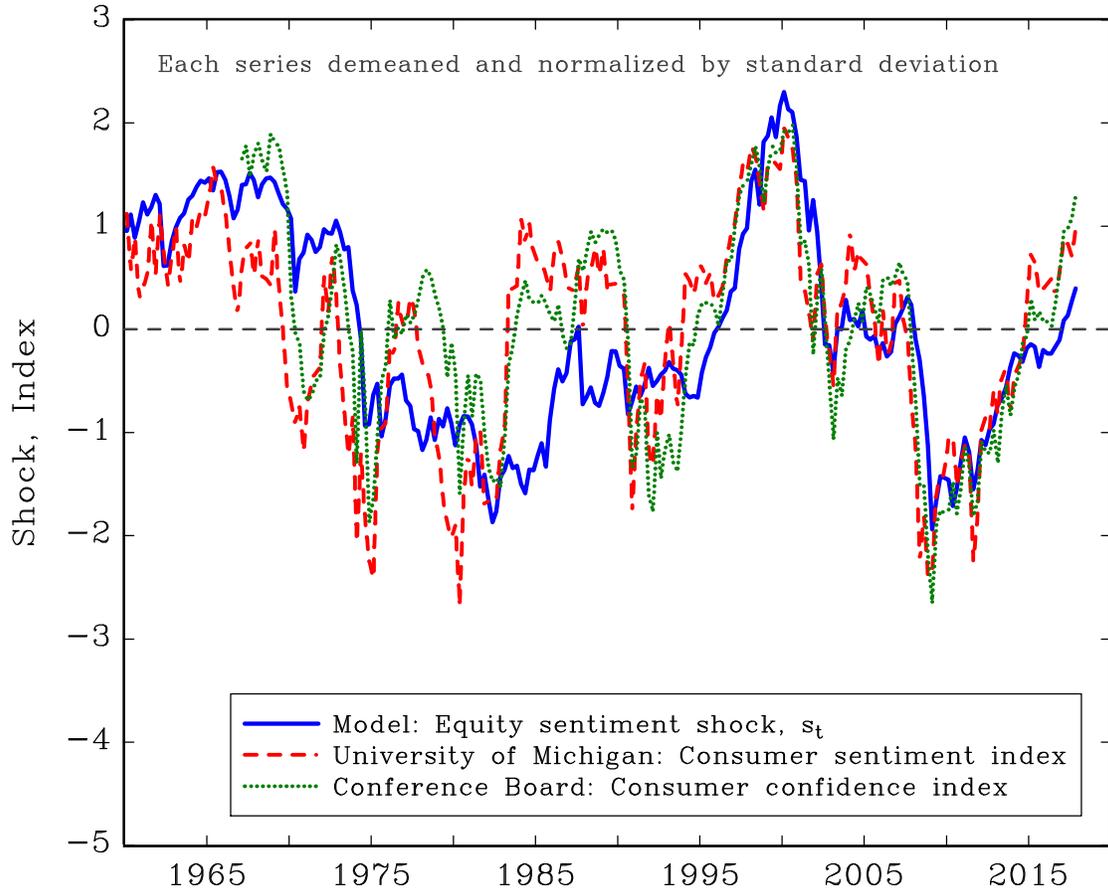


Figure 4: Impulse Responses to Model Equity Sentiment Shock

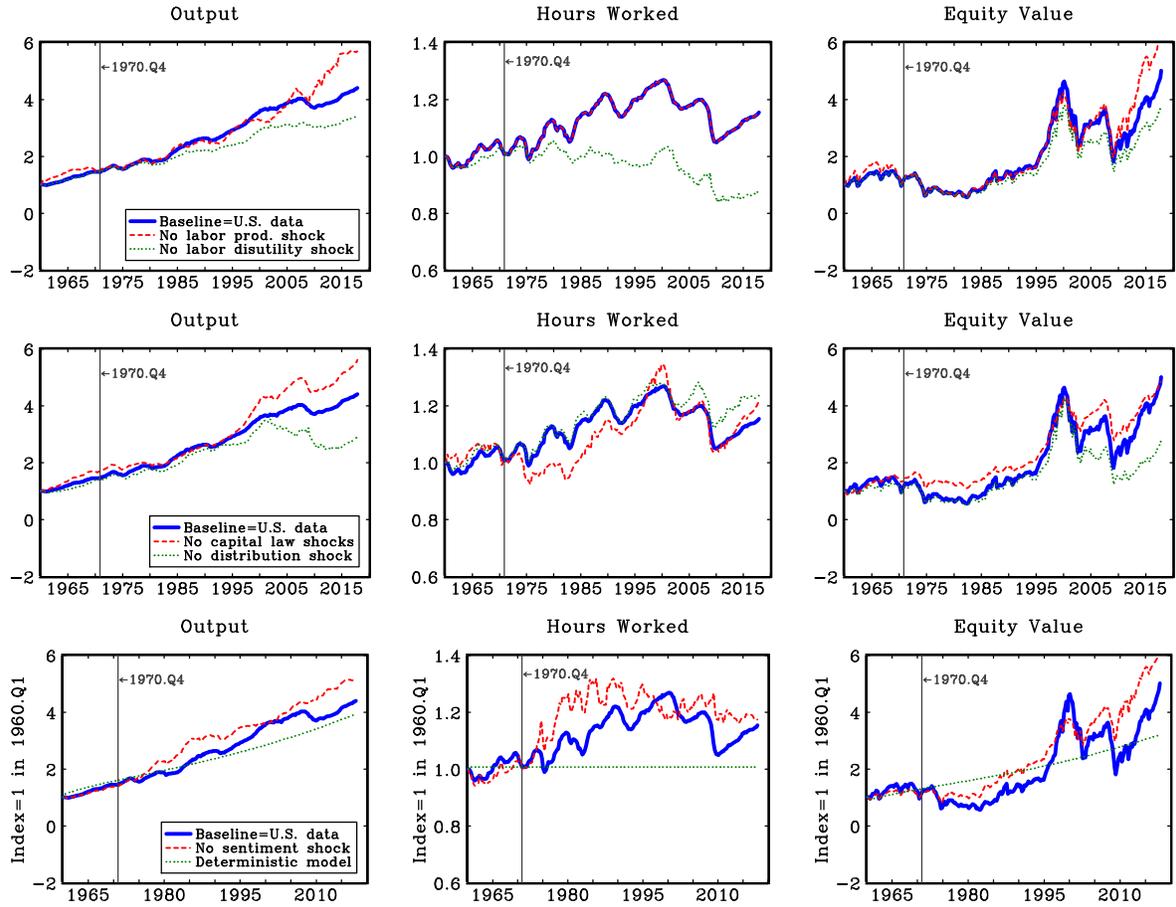
Notes: Movements in the equity sentiment shock capture the notion of animal spirits-driven fluctuations. The panels show the percent deviation of each variable from its no-shock trend. A positive innovation to the equity sentiment shock leads to an immediate increase in output, hours worked, investment, and equity value. But since the capital stock cannot respond immediately, the initial increase in output is not sufficient to allow both consumption and investment to increase on impact. Consumption drops slightly on impact, but then increases with the other variables as the capital stock starts increasing in response to higher investment. Since δ_t is constant here, movements in equity value ($p_t = i_t / \delta_t$) exactly mimic the movements in investment.

Figure 5: *Measures of Sentiment: Model versus U.S. Data*



The model-identified equity sentiment shock is strongly correlated with survey-based measures of U.S. consumer sentiment. The correlation coefficient between s_t and the University of Michigan index is 0.63. The correlation coefficient between s_t and the Conference Board index is 0.71. The figure confirms that it is appropriate to view the model-identified series for s_t as capturing a measure of sentiment.

Figure 6: *Counterfactual Scenarios*



The panels show the effects of shutting off one or more of the various shocks on output (left panels), hours worked (middle panels), and equity value (right panels). A large gap between the model counterfactual path and the U.S. data path (blue line) implies that the omitted shock(s) play an important role in allowing the model variable to match the path of the corresponding U.S. variable.