

Innovations in Growth Potential as Sources of Output and Asset Price Fluctuations

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Abstract

We develop a model where innovations in an economy's growth potential are an important business cycle driving force. The framework shares the emphasis of the recent "new shock" literature on revisions of beliefs about the future as a source of fluctuations, but differs by tying these beliefs to fundamentals of the evolution of the technology frontier. An important feature of the model is that the process of moving to the frontier involves costly technology adoption. In this way, news of improved growth potential has a positive effect on current hours. As we show, the model also has reasonable implications for stock prices. We estimate our model for data post-1984 and show that the innovations shock accounts for nearly a third of the variation in output at business cycle frequencies. The estimated model also accounts reasonably well for the large variation in stock prices over this period. Finally, the endogenous adoption mechanism plays a role in amplifying other shocks.

1 Motivation

A central challenge to modern business cycle analysis is that there are few if any significant primitive driving forces that are readily observable. Oil shocks are perhaps the main example. But even here there is controversy. Not all recessions are preceded by major oil price spikes and there is certainly little evidence that major expansions are fueled by oil price declines. Further, given its low cost share of production, there is debate over whether in fact oil shocks alone could be a source of major output swings. Credit conditions have been a factor in some of the postwar recessions, but not all.

Motivated by the absence of significant observable shocks, an important paper by Beaudry and Portier (2004) proposes that news about the future might be an important source of business cycle fluctuations. Indeed, the basic idea has

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it roots in a much earlier literature due to Beveridge (1909), Pigou (1927), Clark (1934). These authors appealed to revisions in investor's beliefs about future growth prospects to account for business cycle expansions and contractions. A basic fact in support of this general approach is that stock prices movements, while clearly noisy, do tend to lead the cycle (e.g., Stock and Watson, 2002). In addition, Beaudry and Portier refine this evidence by showing that stock prices uncorrelated with current total factor productivity help predict future productivity.

As originally emphasized by Cochrane (1994), however, introducing news shocks within a conventional business cycle framework is a non-trivial undertaking. For example, within the real business cycle framework the natural way to introduce news shocks is to have individual's beliefs about the future path of technology fluctuate. Unfortunately, news about the future path of technology introduces a wealth effect on labor supply that leads to hours moving in the opposite direction of beliefs: Expectation of higher productivity growth leads to a rise in current consumption which in turn reduces labor supply.

This result reflects a second important challenge now for the propagation mechanisms used in standard macroeconomic models. In addition to generating counterfactual responses to shocks about future technology, standard macro models have been traditionally unable to explain the magnitude and co-movement pattern of fluctuations in important variables such as the stock market or the relative price of capital.

Much of the focus of the "news shock" literature to date has focused on introducing new propagation mechanisms that deliver the correct cyclical response of hours. Beaudry and Portier (2004) introduce a two sector model with immobile labor between the sectors. Jaimovich and Rebelo (2008) introduce preferences which dampen the wealth effect on labor supply. However, as Christiano, Ilcig(?), Motto and Rostagno (2008) note, these approaches have difficulty accounting for the high persistence of output fluctuations, as well as the volatility and cyclical behavior of stock prices. These authors instead propose a model based on overly accommodative monetary policy.

In this paper we follow the lead of the news shock literature in developing a framework that emphasizes revisions in beliefs about future growth prospects as key factor in business fluctuations. The framework differs, however, in that news is tied directly to the evolution of fundamentals that govern these prospects. In particular, growth prospects depend on an exogenously evolving technology frontier. Movement to the frontier, however costly. That is, we make the distinction between potential technologies versus those that have been adopted and are usable for production. As in Comin and Gertler (2006), further, we assume that adoption is costly and, on average, a time consuming process.

A shock to the growth rate of potential technologies, accordingly, provides news about the future path of the technology frontier. Unlike in the standard model, however, news about future growth is not simply news of manna from heaven. The new technologies have to be adopted. The desire of firms to adopt new technologies sooner leads to a shift in labor demand when the news about future technology arrive. For reasonable parameterizations, this substitution

effect offsets the wealth effect. Further, this endogenous and procyclical movement of adoption is consistent with the cyclical patterns of diffusion found in Comin (2007). Overall, within endogenous adoption, the hours response to news shocks becomes strictly procyclical. Further, because diffusion of new technologies takes time, the cyclical response to our news shock is highly persistent.

The endogenous adoption mechanisms introduced in our model not only generate reasonable responses to shocks about future technologies but also to the standard macro shocks such as shocks to TFP, government spending, relative price of capital or labor supply.

Even more interesting is the fact that our model broadly captures the cyclical pattern of stock price movements. Unlike standard macro models where the value of the firm is the value of installed capital, in our framework the firm also has the rights to the profit flow of current and future adopted technologies. Revisions in beliefs about this added component of expected earnings allows us to capture both the high volatility of the stock market and its lead over output. Further, because the stock market in our model is anticipating that the earnings from projects that are productive only when they are adopted in the future, the model also has the property that the price-earnings ratio is highly mean reverting, as is consistent with the evidence.

Before proceeding we should emphasize the our approach is close in spirit to a recent paper by Beaudry, Collard and Portier (2007), who similarly emphasize exogenous arrivals of new technologies and endogenous adoption. We differ in details of the technology and adoption process, as well as the empirical implementation. In addition, we emphasize the implications for stock prices, as well as output and investment dynamics.

In section 2 we present a simple expository model to introduce the adoption mechanisms and our news shock as a prelude to an estimated model that we present in section 6. The model adds to a relatively standard real business model an expanding variety of intermediate goods which determines the level of productivity. Though intermediate goods arrive at an exogenous rate, how many can be used in production depends on the agents' adoption decisions.

In section 4 and 5 we calibrate the model and analyze the impact of a shock to the evolution of new technologies. As we noted, assuming rational expectations, this shock reveals news about the economy's future growth potential. As advanced above, our propagation mechanisms yield booms in output, hours, consumption investment and the stock market in response to the news shock.

In section 6, we move to an estimated model. We combine our model of endogenous technology adoption with a variant of the standard quantitative macroeconomic model due to Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2006). We differ mainly by having technological change endogenous whereas in the standard model it is exogenous. Here we want to see whether the quantitative insights we derived from our simple model are robust to a model that provides a reasonable fit of the data. We continue to calibrate the parameters of the adoption process but estimate the same parameters estimated in the literature.

Section 7 reports the estimates. Several findings are worth emphasizing.

First, the implications of our news shock that we found from our simple calibrated model are robust to using a richer estimated model. Second, the shock to the future technology are an important driver of business fluctuations. In particular, they explain 27 percent of output growth (32 percent of HP filtered output). Third, in the historical decomposition, the shocks about future technologies seem to have played a prominent role both in the recessions and in the expansions. Finally, when shocking our model economy with all the estimated shocks, it generates a time series for the stock market which is quite similar to the evolution of the US stock market. Concluding remarks are in section 8.

2 Baseline Model

Our baseline framework is a variation of Greenwood, Hercowitz and Krusell's (2000) business cycle model that features shock to embodied technological change. We treat the process of technological change more explicitly and allow for endogenous technology adoption.

2.1 Resource Constraints

Let Y_t be gross final output, C_t consumption, I_t investment, G_t government consumption, H_t technology adoption expenses and O_t firm overhead operating expenses. Then output is divided as follows:

$$Y_t = C_t + I_t + G_t + H_t + O_t \quad (1)$$

In turn, let J_t be newly produced capital and δ_t be the depreciation rate of capital. Then capital evolve as follows:

$$K_{t+1} = (1 - \delta_t)K_t + J_t \quad (2)$$

Next, let P_t^k be the price of this capital in units of final output which is our numeraire. Given competitive production of final capital goods :

$$J_t = (P_t^k)^{-1} I_t$$

A distinguishing feature of our framework is that P_t^k evolves endogenously. One key source of variation is the pace of technology adoption, which depends on the stock of available new technologies, as well as overall macroeconomic conditions, as we describe below.

2.2 Production

The production of both new capital and output involves two stages. First a continuum of N_t^s (for $s = \{k, y\}$) differentiated firms produce new capital and output, respectively. These firms produce their output by using a continuum of A_t^s (for $s = \{k, y\}$) sector-specific differentiated intermediate goods. Next, we introduce the notation and flesh out this structure of production.

New capital

Final new capital, J_t , is a CES composite of the output of the N_t^K capital good producers, as follows:

$$J_t = \left(\int_0^{N_t^K} J_t(r)^{\frac{1}{\mu^k}} dr \right)^{\mu^k}, \text{ with } \mu^k > 1, \quad (3)$$

where $J_t(r)$ is the output produced by the r^{th} capital producer. Below we describe how N_t^K is determined in equilibrium.

The production of each differentiated capital good, r , involves the combination of new structures ($J_t^s(r)$) and equipment ($J_t^e(r)$) as follows:

$$J_t(r) = (J_t^s(r))^\gamma (J_t^e(r))^{1-\gamma}, \text{ with } \gamma \in (0, 1) \quad (4)$$

We distinguish between equipment investment and other forms of investment, which we generically label "structures", for two reasons. First, as emphasized in Greenwood, Hercowitz and Krusell (2000), embodied technology change influences mainly equipment investment, making it important to disentangle the different forms of capital. Second, based on the data post-1984, equipment investment is more highly correlated with stock price movements. As will become clearer, by tying innovation explicitly to equipment investment, we are better able to capture stock price movements.

To produce equipment, the r capital producer uses the A_t^k intermediate capital goods that have been adopted up to time t . In particular, let $I_t^r(s)$ the amount of intermediate capital from supplier s that producer r demands. Then, he obtains $J_t^e(r)$ units of equipment given by

$$J_t^e(r) = \left(\int_0^{A_t^k} I_t^r(s)^{\frac{1}{\theta}} ds \right)^\theta, \text{ with } \theta > 1.$$

Note that each supplier of intermediate capital goods has a bit of market power. Profit maximization implies that she sets the price of the s^{th} intermediate capital good as a fixed markup θ times the marginal cost of production. Since it takes one unit of final output to produce one unit of intermediate, this marginal cost is unity.

In particular, observe that there are efficiency gains in producing new equipment from increasing the number of intermediate inputs, A_t^k . These efficiency gains are one source of embodied technological change and thus, ultimately, a key source of variation in the relative price of equipment and of the relative price of capital, P_t^k . Shortly, we relate the evolution of A_t^k to an endogenous technology adoption process.

The r^{th} capital producer can obtain a unit of structures from P_{st}^k units of final output, where $p_{st}^k (\equiv \log(P_{st}^k))$ evolves exogenously according to:

$$p_{st}^k = p_{st-1}^k + \varepsilon_{st}$$

where $\psi \in [0, 1]$ and ε_{st} is a stationary first order disturbance. Generally speaking, p_{st}^k , reflects any factors that could affect the cost of producing structures. While efficiency gains could be one of these factors, in contrast to the case of equipment investment, there are no monopoly profits associated with the process, nor is there endogenous diffusion. In addition, p_{st}^k could reflect include other factors reflecting costs of building structures such as credit costs or taxes.

Final output

The composite Y_t is a CES aggregate of N_t^y differentiated final goods, where $Y_t(j)$ is the output of final good producer j :

$$Y_t = \left(\int_0^{N_t^y} Y_t(j)^{\frac{1}{\mu}} dj \right)^{\mu}, \text{ with } \mu > 1, \quad (5)$$

where μ is inversely related to the price elasticity of substitution across goods.

Let $Y_t^j(j)$ be output produced by firm j and $Y_t^j(s)$ the amount of intermediate good the firm employs from supplier s . Then

$$Y_t(j) = \left(\int_0^{A_t^y} Y_t^j(s)^{\frac{1}{\vartheta}} ds \right)^{\vartheta} \quad (6)$$

Intermediate goods used in the output sector are produced using the following Cobb-Douglas technology:

$$Y_t(s) \equiv \int_0^{N_t^y} Y_t^j(s) dj = X_t (U_t(s) K_t(s))^{\alpha} (L_t(s))^{1-\alpha}$$

where X_t is the level of disembodied productivity, U_t denotes the intensity of utilization of capital, and $K_t(s)$ and $L_t(s)$ are the amount of capital and labor rented (hired) to produce the s^{th} intermediate good.

We assume that $x_t (\equiv \log(X_t))$ evolves as follows

$$x_t = x_{t-1} + \varsigma_t$$

where ς_t is first order serially correlated innovation.¹

Following Greenwood, Hercowitz and Huffman (1988), we further assume that a higher rate of capital utilization comes at the cost of a faster depreciation rate, δ . The markets where firms rent the factors of production (i.e. labor and capital) are perfectly competitive.

Free entry

We allow the number of final capital and output producers (i.e. N_t^k and N_t^y) to be endogenously determined by a free entry condition in order to generate high frequency variation in the real price of capital that is consistent with the evidence. As will become clear, we will be able to decompose P_t^k into the

¹For simplicity, we assume that it is exogenous. It is quite straightforward to endogenize it as shown in Comin and Gertler (2006).

product of two terms: the wholesale price \bar{P}_t^k that is governed exclusively by technological conditions and a "markup" P_t^k/\bar{P}_t^k that is instead governed by cyclical factors.

We assume that the per period operating cost of a final producer, o_t^s is

$$o_t^s = b^s \bar{P}_t^s K_t, \text{ for } s = \{y, k\}$$

where b^s is a constant, \bar{P}_t^k is the wholesale price of capital and K_t is the aggregate capital stock. That is, the operating costs grow with the replacement value of the capital stock in order to have balanced growth. As in Comin and Gertler (2006), we think of operating costs as increasing in the technological sophistication of the economy, as measured by $\bar{P}_t^k K_t$. At the margin, the profits of capital producers must cover this operating cost. Free entry pins down N_t^k and N_t^y , as shown below.

2.3 Technology

The efficiency of production depends on the exogenous productivity variables (X_t , and P_{st}^k) and on the number of "adopted" intermediate goods in the production of capital, A_t^k , and final output, A_t^y . We characterize next the process that governs the evolution of these variables.

New intermediate goods

Prototypes of new intermediate goods arrive exogenously to the economy.² Upon arrival, they are not yet usable for production. In order to be usable, a new prototype must be successfully adopted. The adoption process, in turn, involves a costly investment that we describe below. We also allow for obsolescence of these products.

Let Z_t^s denote the total number of intermediate goods in sector s (for $s = \{k, y\}$). at time t . Note that Z_t^s includes both previously adopted goods and "not yet adopted" prototypes. The law of motion for Z_t^s is as follows:

$$Z_{t+1}^s = (\bar{\chi}_s \chi_t^{\xi_s} + \phi) Z_t^s \quad (7)$$

where ϕ is the fraction of intermediate goods that do not become obsolete, and χ_t determines the stochastic growth rate of the number of prototypes and is governed by the following AR(1) process

$$\chi_t = \rho \chi_{t-1} + \varepsilon_t$$

where ε_t is a white noise disturbance. In addition, we normalize the elasticity of new technologies with respect to the innovation shock in the capital sector ξ_k at unity. Though we allow ξ_y to differ from unity.

²An alternative way to introduce shocks to future technologies is to introduce a R&D sector (as in Comin and gertler, 2006) with stochastic productivity of the R&D investments. This more elaborated framework yields very similar results to ours.

Note that the shock to the growth rate of intermediate goods is the same across sectors. However, the effect of the shock on the stock of technologies within a sector, measured by the slope coefficient $\bar{\chi}_s$ and the elasticity ξ_s , differs across sectors. Here we wish to capture the idea of spillovers in the innovation process: Innovations that lead to new equipment often make possible new disembodied innovations. For example, the IT revolution made possible e-commerce. It also accelerated the offshoring process and improved the efficiency of inventories management, and so on.

Evidence of this spillover appears in the data: At medium frequencies, movements in relative equipment prices are correlated with movements in TFP. As we show shortly, given that a component of TFP in our model is exogenous, we can calibrate the parameters of the innovation process to capture this correlation, as well as the long run difference between growth in TFP and equipment prices.

We emphasize that in this framework, news about future growth prospects is captured by innovations in χ_t , which governs the growth of potential new intermediate goods. Realizing the benefits of these new technologies, however, requires a costly adoption process that we turn to next.

Adoption (Conversion of Z to A)

At each point in time a continuum of unexploited technologies is available to adopt. Through a competitive process, firms that specialize in adoption try to make these technologies usable. These firms, which are owned by households, spend resources attempting to adopt the new goods, which they can then sell on the open market. They succeed with an endogenously determined probability λ_t^s , for $s = \{k, y\}$. Once a technology is usable, all capital producing firms are able to employ it immediately.

Note that under this setup there is slow diffusion of new technologies on average (as they are slow on average to become usable) but aggregation is simple as once a technology is in use, all firms have it. Consistent with the evidence,³ we will obtain a pro-cyclical adoption behavior by endogenizing the probability λ_t^s that a new technology becomes usable and making it increasing in the amount of resources devoted to adoption at the firm level.

Specifically, the adoption process works as follows. To try to make a prototype usable at time $t + 1$, at t an adopting firm spends h_t^s units of final output. Its success probability λ_t^s is increasing in adoption expenditures, follows:

$$\lambda_t^s = \lambda(\Gamma_t^s h_t^s)$$

with $\lambda' > 0$, $\lambda'' < 0$, where h_t^s are the resources devoted to adopting one technology in time t and where Γ_t is a factor that is exogenous to the firm, given by

$$\Gamma_t^s = A_t^s / o_t^s$$

We presume that past experience with adoption, measured by the total number of projects adopted A_t^s , makes the process more efficient. In addition to having

³Comin (2007).

some plausibility, this assumption ensures that the fraction of output devoted to adoption is constant along the balanced growth path.

The value to the adopter of successfully bringing a new technology into use, v_t^s , is given by the present value of profits from operating the technology. Profits π_t^s arise from the monopolistic power of the producer of the new good. Accordingly, given that $\beta\Lambda_{t,t+1}$ is the adopter's stochastic discount factor for returns between $t+1$ and t , we can express, v_t^s , as

$$v_t^s = \pi_t^s + \phi E_t [\beta\Lambda_{t,t+1}v_{t+1}^s]. \quad (8)$$

If an adopter is unsuccessful in the current period, he may try again in the subsequent periods to make the technology usable. Let j_t^s be the value of acquiring an innovation that has not yet been adopted yet. j_t^s is given by

$$j_t^s = \max_{h_t^s} -h_t^s + E_t\{\beta\Lambda_{t,t+1}\phi[\lambda_t^s v_{t+1}^s + (1-\lambda_t^s)j_{t+1}^s]\} \quad (9)$$

Optimal investment in adopting a new technology is given by:

$$1 = E_t [\beta\Lambda_{t,t+1}\phi\Gamma_t\lambda^{s'}(\Gamma_t^s h_t^s)(v_{t+1}^s - j_{t+1}^s)] \quad (10)$$

It is easy to see that h_t^s is increasing in $v_{t+1}^s - j_{t+1}^s$, implying that adoption expenditures, and thus the speed of adoption, are likely to be procyclical. Note also that the choice of h_t^s does not depend on any firm specific characteristics. Thus in equilibrium, the success probability is the same for all firms attempting adoption.

2.4 Households

Our formulation of the household sector is reasonably standard. In particular, there is a representative household that consumes, supplies labor and saves. It may save by either accumulating capital or lending to innovators and adopters. The household also has equity claims in all monopolistically competitive firms. It makes one period loans to adopters and also rents capital that it has accumulated directly to firms.

Let C_t be consumption. Then the household maximizes the present discounted utility as given by the following expression:

$$E_t \sum_{i=0}^{\infty} \beta^i \left[\ln C_{t+i} - \mu^w \frac{(L_{t+i})^{1+\zeta}}{1+\zeta} \right] \quad (11)$$

with $\zeta > 0$. The budget constraint is as follows:

$$C_t = W_t L_t + \Pi_t + [D_t + P_t^k]K_t - P_t^k K_{t+1} + R_t B_t - B_{t+1} - T_t \quad (12)$$

where Π_t reflects the profits of monopolistic competitors paid out fully as dividends to households, B_t is total loans the households makes at $t-1$ that are payable at t , and T_t reflects lump sum taxes which are used to pay for government expenditures. The household's decision problem is simply to choose

consumption, labor supply, capital and bonds to maximize equation (11) subject to (12).

3 Symmetric equilibrium

The following relationships hold in the symmetric equilibrium of this economy:

Evolution of endogenous states, K_t and A_t^y and A_t^k :

$$K_{t+1} = (1 - \delta(U_t))K_t + (P_t^K)^{-1}I_t \quad (13)$$

$$A_{t+1}^s = \lambda_t^s[Z_t^s - A_t^s] + \phi A_t^s, \text{ for } s = \{k, y\} \quad (14)$$

where the evolution of the stock of new technologies in each sector, Z_t^s , is given by equation (7).

Resource Constraint:

$$Y_t = C_t + G_t + \frac{P_t^k J_t}{\mu_k \theta} + \overbrace{\frac{\mu - 1}{\mu} Y_t + \frac{\mu_k - 1}{\mu_k} I_t}^{\text{Entry Costs}} + \sum_{s=\{k,y\}} \overbrace{(Z_t^s - A_t^s) h_t^s}^{\text{Adoption Costs}} \quad (15)$$

Aggregate production

$$Y_t = X_t (A_t^y)^{\vartheta-1} (N_t^y)^{\mu-1} (U_t K_t)^\alpha L_t^{1-\alpha} \quad (16)$$

where total factor productivity, $X_t (A_t^y)^{\vartheta-1} (N_t^y)^{\mu-1}$, depends on the stock of adopted intermediate output goods A_t^y .

Factor market equilibria for L_t , and U_t :

$$(1 - \alpha) \frac{Y_t}{L_t} = \mu \mu^w L_t^\zeta / (1/C_t) \quad (17)$$

$$\alpha \frac{Y_t}{U_t} = \mu \delta'(U_t) P_t^K K_t \quad (18)$$

Investment in equipment and structures:

$$\frac{I_t^e}{I_t^s} = \frac{1 - \gamma}{\gamma}$$

where

$$\begin{aligned} I_t^e &= P_t^e J_t^e \\ I_t^s &= P_t^s J_t^s \end{aligned}$$

and the price of equipment, P_t^e , is defined below.

Consumption/Saving

$$E_t\{\beta\Lambda_{t+1} \cdot [\alpha \frac{Y_{t+1}}{\mu K_{t+1}} + (1 - \delta(U_{t+1})P_{t+1}^K)/P_t^k]\} = 1 \quad (19)$$

where $\Lambda_{t+1} = C_t/C_{t+1}$.

Optimal adoption of innovations in sector $s = \{k, y\}$

$$1 = \phi\beta E_t \left[\Lambda_{t+1} \frac{A_t^s}{o_t^s} \lambda' \left(\frac{A_t^s}{o_t^s} h_t^s \right) (v_{t+1}^s - j_{t+1}^s) \right] \quad (20)$$

with

$$v_t^s = \pi_t^s + \phi\beta E_t [\Lambda_{t+1} v_{t+1}^s]$$

and

$$\begin{aligned} \pi_t^k &= (1 - \frac{1}{\theta})(1 - \gamma) \frac{I_t}{A_t^k \mu_k} \\ \pi_t^y &= (1 - \frac{1}{\vartheta}) \frac{Y_t}{A_t^y \mu} \end{aligned}$$

$$j_t^s = -h_t^s + \phi\beta E_t [\Lambda_{t+1} [\lambda_t^s v_{t+1}^s + (1 - \lambda_t^s) j_{t+1}^s]]$$

where

$$\lambda_t^s = \bar{\lambda}^s \left(\frac{A_t^s h_t^s}{o_t^s} \right)^{\rho_\lambda}$$

Free entry into production of final goods and final capital goods:

$$\begin{aligned} \frac{\mu - 1}{\mu} \frac{Y_t}{N_t^y} &= o_t^y \\ \frac{\mu_k - 1}{\mu_k} \frac{I_t}{N_t^k} &= o_t^k \end{aligned} \quad (21)$$

Relative price of retail and wholesale capital

$$P_t^K = \mu_k (N_t^k)^{-(\mu_k - 1)} (P_{st}^K)^\gamma (P_{et}^K)^{1-\gamma} \quad (22)$$

where P_{et}^K is equal to

$$P_{et}^K = \theta (A_t^k)^{-(\theta - 1)}$$

and the wholesale price of capital is

$$\bar{P}_t^K = \theta^{(1-\gamma)} (A_t^k)^{-(1-\gamma)(\theta-1)} (P_{st}^K)^\gamma$$

Observe that the wholesale price of capital varies inversely with the number of adopted technologies. The same is thus true for the retail price. However, the retail price also varies at the high frequency with entry. The gains from agglomeration introduces efficiency gains in the production of new capital in

booms and vice-versa in recessions. This leads to countercyclical movements in P_t^K at the high frequency. At the medium and low frequencies, endogenous technology adoption is responsible for countercyclical movements in P_t^K .

Finally, we are now in a position to get a sense of how "news" about technology plays out in this model. Consider first the standard model where both embodied and disembodied technological change is exogenous. News of a future decline in the relative price of capital or increase in total factor productivity leads to the expectation of higher labor productivity in the future. Current consumption increases, inducing a negative effect on labor supply, as equation (17) suggests. Since current labor productivity does not increase, the net effect of the positive news shock is to reduce hours. By construction, in our model the news is of improved technological prospects as opposed to improved technology per se. When those prospects are realized depends on the intensity of adoption. Hence, the good news in this framework sparks a contemporaneous rise in aggregate demand driven by the desire to increase the speed of adoption. This substitution effect, in turn, leads to a higher demand for capital and labor offsetting the wealth effect. As a result hours, investment and output increase in response to the positive technology prospects. Next we present some simulations that illustrates how our framework can induce a procyclical movements in these variables in response to innovation shocks.

4 Model Simulations of "Innovation" Shocks

In this section we first calibrate our model and then present simulations of the impact of an innovation in the growth rate of new intermediate goods. As we have been noting, one can interpret this shock as capturing news about the economy's growth potential.

4.1 Calibration

The calibration we present here is meant as a reasonable benchmark that we use to illustrate the qualitative and quantitative response of the model to a shock about future technologies. These responses are very robust to reasonable variations around this benchmark. In section 5, we will estimate the values of some of these parameters. To the extent possible, we use the restrictions of balanced growth to pin down parameter values. Otherwise, we look for evidence elsewhere in the literature. There are a total of eighteen parameters. Ten appear routinely in other studies. The eight others relate to the adoption processes and also to the entry/exit mechanism.

We begin with the standard parameters. A period in our model corresponds to a quarter. We set the discount factor β equal to 0.98, to match the steady state share of non-residential investment to output. Based on steady state

evidence we also choose the following numbers: (the capital share) $\alpha = 0.35$; (the equipment share) $(1-\gamma) = 0.17/0.35$; (government consumption to output) $G/Y = 0.2$; (the depreciation rate) $\delta = 0.015$; and (the steady state utilization rate) $U = 0.8$.⁴ We set the inverse of the Frisch elasticity of labor supply ζ at unity, which represents an intermediate value for the range of estimates across the micro and macro literature. Similarly, we set the elasticity of the change in the depreciation rate with respect the utilization rate, $(\delta''/\delta')U$ at 0.15 following Rebelo and Jaimovich (2006). Finally, based on evidence in Basu and Fernald (1997), we fix the steady state gross valued added markup in the final output, μ , equal to 1.1 and the corresponding markup for the capital goods sector, μ^k , at 1.15.

We next turn to the “non-standard” parameters. To approximately match the operating profits of publicly traded companies, we set the gross markup charged by intermediate capital (θ) and output goods (ϑ) to 1.4 and 1.25, respectively. Following Caballero and Jaffe (1992), we set ϕ to 0.99, which implies an annual obsolescence rate of 4 percent. The steady state growth rate of the relative price of capital, depends on $\bar{\chi}_k$, the markup θ , the obsolescence rate and ξ_k . We normalize ξ_k to 1. To match the average annual growth rate of the Gordon quality adjusted price of equipment relative to the BEA price of consumption goods and services (-0.035), we set $\bar{\chi}_k$ to 3.04 percent.

ξ_y affects the correlation between TFP growth and the growth rate of the relative price of equipment. Many other variables affect this correlation in the short run. However, these other forces are likely to have virtually no effect over them in the medium term (i.e. cycles with periods between 8 and 50 years). Under this premise, and a log-linear approximation, the covariance between medium term growth in TFP and the relative price of equipment and their variances depend on the variance of χ_t , the variance of x_t and ξ_y . Hence, we can use these three moments in the data to identify ξ_y . This yields an estimate for ξ_y of approximately 0.6. Our results are quite robust to variation in ξ_y between 0.5 and 0.8.

The growth rate of GDP in steady state depends on the growth rate of capital and on the growth rate of intermediate goods in the output sector. To match the average annual growth rate of GDP per working age person over the postwar period (0.024) we set $\bar{\chi}_y$ to 2.02 percent.

For the time being, we also need to calibrate the autocorrelation of the shock to future technologies. When we estimate the model, this will be one of the parameters we shall estimate. One very crude proxy of the number of prototypes that arrive in the economy is the number of patent applications. The autocorrelation of the annual growth rate in the stock of patent applications is 0.95. This value is consistent with the estimate we obtain below and is the value we use to calibrate the autocorrelation of χ_t .

We now consider the parameters that govern the adoption process. We use

⁴We set U equal to 0.8 based on the average capacity utilization level in the postwar period as measured by the Board of Governors.

two parameters to parameterize the function $\lambda^s(\cdot)$ as follows:

$$\lambda_t^s = \bar{\lambda}^s \left(\frac{A_t^s h_t^s}{o_t^s} \right)^{\rho_\lambda}$$

These are $\bar{\lambda}^s$ and ρ_λ . To calibrate these parameters we try to assess the average adoption lag and the elasticity of adoption with respect to adoption investments. Estimating this elasticity is difficult because we do not have good measures of adoption expenditures, let alone adoption rates. One partial measure of adoption expenditures we do have is development costs incurred by manufacturing firms trying that make new capital goods usable (which is a subset of the overall measure of R&D that we used earlier. A simple regression of the rate of decline in the relative price of capital (the relevant measure of the adoption rate of new embodied technologies in the context of our model) on this measure of adoption costs and a constant yields an elasticity of 0.9. Admittedly, this estimate is crude, given that we do not control for other determinants of the changes in the relative price of capital. On the other hand, given the very high pro-cyclicality of the speed of adoption estimated by Comin (2007), we think it provides a plausible benchmark value.

Given the discreteness of time in our model, the average time to adoption for any intermediate good is approximately $1/\lambda + 1/4$. Mansfield (1989) examines a sample of embodied technologies and finds a median time to adoption of 8.2 years. However, there are reasons to believe that this estimate is an upper bound for the average diffusion lag. First, the technologies typically used in these studies are relatively major technologies and their diffusion is likely to be slower than for the average technology. Second, most existing studies oversample older technologies which have diffused slower than earlier technologies.⁵ For these reasons, we set $\bar{\lambda}^s$ to match an average adoption lag of 5 years and a quarter.⁶

We next turn to the entry/exit mechanism. We set the overhead cost parameters so that the number of firms that operate in steady state in both the capital goods and final goods sector is equal to unity, and the total overhead costs in the economy are approximately 10 percent of GDP.

4.2 Model Simulations

Here we illustrate how introducing the endogenous adoption of technologies affects the model's response to a news shock about future technology. Figure 1 shows the impulse response functions for both our model (solid) and for a version of our model without endogenous adoption and entry (dashed). That is, a version where new intermediate goods diffuse at a fixed speed and where N_t^s are fixed for both $s = \{k, y\}$.

⁵Comin and Hobijn (2007) and Comin, Hobijn and Rovito (2008).

⁶It is important to note that, as shown in Comin (2008), a slower diffusion process increases the amplification of the shocks from the endogenous adoption of technologies because it increases the stock of technologies waiting to be adopted in steady state. In this sense, by using a higher speed of technology diffusion than the one estimated by Mansfield (1989) and others we are being conservative in showing the power of our mechanism.

The main observation is that, while the positive news about future technology lead to a contraction in output in the model without exogenous adoption, once adoption is endogenous, this same shock generates an output boom. This increase in output is driven by an increase in hours worked, in the utilization rate and by the entry of final output producers.

Hours increases in response to the increment in the real wage, which in this model is proportional to labor productivity. This increment in the real wage results from an increase in labor demand driven by the increased expenditure on adoption of new technologies along with associated increases in both investment and consumption demand.

Adoption expenses increase for two reasons. First, the shock increases the number of unadopted technologies. Hence, more resources are necessary to adopt the stock of not adopted technologies at the same speed as before. But, the present discounted value of future profits from selling an adopted technology, v_t , also increases. Hence, it is optimal to adopt technologies faster as illustrated by the increase in λ_t .

The increase in aggregate output raises the return to capital inducing an investment boom. The investment boom leads to entry in the production of differentiated capital goods. The efficiency gains from the variety of final capital goods, lead to an initial decline in the relative price of capital. This effect is short lived since investment declines quickly. The acceleration in the speed of adoption of new intermediate capital goods is responsible for the decline in the relative price of capital over the medium and long term.

These dynamics of the price of capital propagate the effect of the shock into the medium and long run. In Figure 1 we can see how, despite the fact that after 20 quarters, the shock, χ_t , has declined by 60 percent, the relative price of capital is at the same level as when the shock impacted the economy. Hence, the endogenous adoption of technologies greatly enhances the persistence of macro variables.

The output boom is further amplified by the entry of final goods producers which, given the gains from variety, increase the efficiency of production. Similarly, the increase in the utilization rate also amplifies the initial response to the shock. Specifically, a way to satisfy the higher aggregate demand is by utilizing more intensively the existing capital stock. In addition to a higher marginal value of utilization, the lower relative price of capital also reduces the marginal cost of utilizing more intensively the capital stock contributing to the raise in utilization.

In contrast to this, the model with a fixed speed of technology diffusion lacks the mechanism that induces agents to switch away from leisure upon the arrival of the positive news about future technology. This decline in hours worked leads to a recession and to a decline in hours worked and capacity utilization. The wealth effect, however, leads to a small initial increase in consumption.

5 The stock market

As Beaudry and Portier (200?) emphasize, any news-driven theory of business fluctuations must account for the large movements in the stock market that anticipate the output fluctuations. In conventional models, it is difficult to generate large procyclical movements in stock prices. One problem is that in models with embodied technological as well as in the data, the relative price of capital tends to move countercyclically. Of course, by introducing some form of adjustment costs, it is possible to generate procyclical movements in the market price of installed capital. However, absent counterfactually high adjustment costs it is very difficult to generate empirically reasonable movements in market prices of capital.

As Hall (200x) and others have emphasized, the value of corporations is larger than the value of their installed capital. This opens a new possibility for large movements in asset prices. Our model provides a theory of this intangible capital. Specifically, it is linked to the rights to make a profit out of current and future adopted intermediate goods. While the relative price of capital (and hence the value of the capital stock) are very counter-cyclical, profits and the arrival of intermediate goods are very pro-cyclical. This opens a natural route to explaining the stock market as a highly volatile leading indicator of output movements. Next, we formalize this intuition.

Within our framework, the value of the stock market Q_t is composed of four terms, as the following expression indicates.

$$\begin{aligned}
 Q_t = & \overbrace{P_t^k K_t}^{\text{Replacement value of capital}} + \sum_{s=\{k,y\}} \overbrace{A_t^s (v_t^s - \pi_t^s)}^{\text{Value of adopted technologies}} \\
 & + \sum_{s=\{k,y\}} \overbrace{(j_t^s + h_t^s)(Z_t^s - A_t^s)}^{\text{Value of existing not adopted technologies}} + E_t \left[\sum_{s=\{k,y\}} \overbrace{\sum_{\tau=t+1}^{\infty} \Lambda_{\tau} j_{\tau}^s (Z_{\tau}^s - \phi Z_{\tau-1}^s)}^{\text{Value of future non-adopted technologies}} \right]
 \end{aligned} \tag{23}$$

First, the market values the capital stock installed in firms. This is captured by the first term. Since capital is a stock, the short run evolution of this first term is driven by the dynamics of the price of capital. As we have argued above, the price of capital will be counter-cyclical and so will be the first term in (23). The second term reflects the market value of adopted intermediate goods and therefore currently used to produce new capital and output. The third term corresponds to the market value of existing intermediate goods which have not yet been adopted. The final term captures the market value of the intermediate goods that will arrive in the future. The rents associated with the arrival of these prototypes also have a value which is captured by the market.

One complication when comparing the model's predictions to the data is that we do not have information on the value of all the companies in the economy, current and future. In reality we only have information about the market

value of publicly traded companies which may complicate comparing the model predictions about the value of companies with the data. One issue is that share of publicly traded companies may vary over the cycle. This share, however, is likely to be procyclical (i.e. IPOs are pro-cyclical) which would induce an upward bias in the measured cyclicity of the stock market value. A second complication would arise if the share of the different components of expression (23) in the value of publicly traded companies differed a lot from their share in the value of non-publicly traded companies. A priori, there is no good reason to believe that this is the case. In spite of this, we have checked for the robustness of the main predictions of the model to reasonable variations in the importance of the different components of (23) between public and private companies.

Figure 2 displays the response of the relative price of capital and the stock market as measured by (23) to a unit shock to the news about future technologies, χ_t . We also report the response of each of its four components and the response of the price dividend ratio.

As anticipated above, the stock market experiences a strong boom in response to the news shock while the relative price of capital declines. The stock market goes up because the total value of existing adopted technologies, and existing and future not adopted technologies increases in response to both an increase in their demand and in the number of intermediate goods available. The decline in the relative price of capital reduces the replacement cost of physical capital leading to a drop in the first term in (23). However, this decline is more than compensated by the increase in the other three terms.

Comparing Figures 1 and 2 yields two interesting observations. First, the stock market moves much more than output (between 10 and 15 times more). This is consistent with the evidence. Second, the stock market leads output since it incorporates the value of future profits which strongly co-move with output. The response of the market to the news about future technology is persistent but leads to a monotonic decline in the market after the realization of the news. The higher volatility of the market also creates a mean-reverting pattern for the price-dividend ratio which is consistent with the evidence (REF).

6 An Extended Model for the Estimation

In this section generalize our model and then estimate it. We add some key features that have proven to be helpful in permitting the conventional macroeconomic models (e.g. Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2006)) capture the data. Our purpose here is twofold. First we wish to assess whether the effects of our news shock that we identified in our baseline model are robust in a framework that provides an empirically reasonable description of the data. Second, by proceeding this way, we can formally assess the contribution of our innovation shock as we have formulated them to overall business cycle volatility.

6.1 The Extended Model

The features we add include: habit formation in consumption, flow investment adjustment costs, nominal price stickiness in the form of staggered price setting, and a monetary policy rule.

To introduce habit formation, we modify household preferences to allow utility to depend on lagged consumption as well as current consumption in the following simple way:

$$E_t \sum_{i=0}^{\infty} \beta^i b_{t+i} \left[\ln(C_{t+i} - vC_{t+i-1}) - \mu_{t+i}^w \frac{(L_{t+i})^{1+\zeta}}{1+\zeta} \right] \quad (24)$$

where the parameter v , which we estimate, measures the degree of habit formation. In addition, the formulation allows for two exogenous disturbances: b_t is a shock to household's subjective discount factor and μ_t^w is a shock to the relative weight on leisure. The former introduces a disturbance to consumption demand and the latter to labor supply. Overall, we introduce a number of shocks equal to the number of variables we use in the estimation in order to obtain identification.

Adding flow adjustment costs leads to the following formulation for the evolution of capital:

$$K_{t+1} = (1 - \delta_t)K_t + J_t \left(1 - \gamma \left(\frac{J_t}{(1 + g_K)J_{t-1}} - 1 \right)^2 \right) \quad (25)$$

where γ , another parameter we estimate, measures the degree of adjustment costs. We note that these adjustment costs are external and not at the firm level. Capital is perfectly mobile between firm. In the standard formulation (e.g. Justiniano, Primiceri, and Schaumburg (2008)), the relative price of capital is an exogenous disturbance. In our model it is endogenous. As equation (??) suggests, P_t^k depends inversely on the volume of adopted technologies A_t^k and the cyclical intensity of production of new capital goods, as measured by N_t^k .

We model nominal price rigidities by assuming that the monopolistically competitive intermediate goods producing firms (see equation (5)) set prices on a staggered basis. For convenience, we fix the number of these firms at the steady state value N . Following Smets and Wouters (2006) and Justiniano, Primiceri and Schaumburg (2008), we used a formulation of staggered price setting due to (1983), modified to allow for partial indexing. In particular, every period a fraction $1 - \xi$ are free to optimally reset their respective price. The fraction ξ that are not free to optimally choose instead adjust price according to a simple indexing rule based on lagged inflation. Let $P_t(j)$ be the nominal price of firm j 's output, P_t the price index and $\Pi_{t-1} = P_t/P_{t-1}$ the inflation rate. Then the indexing rule is given by:

$$P_{t+1}(j) = P_t(j) (\Pi_t)^{\iota_p} (\Pi)^{1-\iota_p} \quad (26)$$

where Π and ι_p are parameters that we estimate: the former is the steady state rate of inflation and the latter is the degree of partial indexation. The fraction

of firms that are free to adjust, choose the optimal reset price P_t^* to maximize expected discounted profits given by.

$$E_t \sum_{s=0}^{\infty} \xi^s \beta^s \Lambda_{t,s} \left\{ \left[\frac{P_t^*}{P_{t+s}} \left(\prod_{j=0}^s (\Pi_{t+j})^{\iota_p} (\Pi)^{1-\iota_p} \right) \right] Y_{t+s}(j) - W_{t+s} N_{t+s}(j) - D_{t+s} K_{t+s}(j) \right\} \quad (27)$$

given the demand function for firm j 's product (obtained from cost minimization by final goods firms):

$$Y_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{\frac{-\mu}{\mu-1}} Y_t \quad (28)$$

Given the law of large numbers and given the price index, the price level evolves according to

$$P_t = [(1 - \xi)(P_t^*)^{\frac{\mu-1}{\mu}} + \xi(P_{t-1})^{\frac{\mu-1}{\mu}}]^{\frac{\mu}{\mu-1}} \quad (29)$$

Finally, define R_t^n as the nominal rate of interest, defined by the Fisher relation $R_{t+1} = R_t^n E_t \Pi_{t+1}$. The central bank sets the nominal interest rate R_t^n according to a simple Taylor rule with interest rate smoothing, as follows:

$$\frac{R_t^n}{R^n} = \left(\frac{R_{t-1}^n}{R^n} \right)^{\rho_r} \left(\left(\frac{\Pi_t}{\Pi} \right)^{\phi_p} \left(\frac{Y_t}{Y_t^0} \right)^{\phi_y} \right)^{1-\rho_r} \exp(\mu_{mp,t}) \quad (30)$$

where R^n is the steady state of the gross nominal interest rate and Y_t^0 is trend output, and $\mu_{mp,t}$ is an exogenous shock to the policy rule.

Including habit formation and flow investment adjustment costs give the model more flexibility to capture output, investment and consumption dynamics. We include nominal rigidities and a Taylor rule for two reasons. First, doing so allows us to use the model to identify the real interest rate which enters the first conditions for both consumption and investment. The nominal interest rate is observable but expected inflation is not. However, from the model we identify expected inflation. Second, having monetary policy allows us to evaluate the contribution of the monetary policy rule to the propagation of innovation shocks, similar in spirit to what Christiano, ? , Motto and Rostagno (2007) emphasize for news shocks.

One widely employed friction that we do not add is nominal wage rigidity. While adding this feature would help improve the ability of the model in certain dimensions, we felt that at least for this initial pass at the data, the cost of added complexity outweighed the marginal gain in fit.

We emphasize that the critical difference in our framework is the endogenous component of both embodied and disembodied productivity. The standard model treats the evolution of both of these phenomena as exogenous disturbances. In our model the key primitive is the innovation process. Shocks to this process influence the pace of new technological opportunities which are realized only by a costly adoption process.

7 Estimation

7.1 Data and Estimation Strategy

We estimate the model using quarterly data from 1984:I to 2008:II on seven key macroeconomic variables in the US economy: output, consumption, equipment investment, non-equipment investment, inflation, nominal interest rates and hours. The vector of observable variables is:

$$[\Delta \log Y_t \quad \Delta \log C_t \quad \Delta \log I_t^e \quad \Delta \log I_t^s \quad R_t \quad \Pi_t \quad \log(L_t)]$$

The standard models typically include real wage growth. However, since we abstract from wage rigidity we do not include this variable in the estimation.

Following Smets, and Wouters (2007) and Primiceri et al. (2006 and 2008), we construct real GDP by dividing the nominal series (GDP) by population and the GDP Deflator. Real series for consumption and investment in equipment and structures are obtained similarly. Consumption corresponds only to personal consumption expenditures of non-durables and services; while non-equipment investment includes durable consumption, structures, change in inventories and residential investment. Labor is the log of hours of all persons divided by population. The quarterly log difference in the GDP deflator is our measure of inflation, while for nominal interest rates we use the effective Federal Funds rate. Because we allow for non-stationary technology growth, we do not demean or detrend any series.

The model contains seven structural shocks. Five appear in the standard models. These include shocks to: the household's subjective discount factor, the household's preference for leisure, government consumption; the monetary policy rule, and the growth rate of TFP. The key new shock in our model is the disturbance to the growth rate of potential new intermediate capital goods, which we refer to as an "innovation" shock. Since this shock signals opportunities for future growth, it is also similar in spirit to a "news" shock. Finally, we allow for an exogenous shock to the cost of producing non-equipment investment, but are agnostic about the deep underlying source of this shock.

We continue to calibrate the parameters of the embodied technology process. However, we estimate the rest of the parameters of the model, all of which appear in the standard quantitative macroeconomic framework. In particular, we estimate are the parameters that capture habit persistence, investment adjustment costs, elasticity of utilization of capital, labor supply elasticity and the feedback coefficients of the monetary policy rule. We also estimate the persistence and standard deviations of the shock processes.

We use Bayesian estimation to characterize the posterior distribution of the structural parameters of the model (see An and Schorfheide (2005) for a survey). That is, we combine the prior distribution of the parameters with the likelihood of the model to obtain the posterior distribution of each model parameter.

7.1.1 Priors and Posterior Estimates

Table 2 presents the prior distributions for the structural parameters along with the posterior estimates. Tables 3 presents the same information for the estimates of the serial correlation and standard deviation of the stochastic processes. To maintain comparability with the literature, for the most part we employ the same priors as in Justiniano, Primiceri and Schaumberg (2007).

For the most part, the parameter estimates are very close to what has been obtained elsewhere in the literature (e.g. Smets and Wouters (2006), Justiniano, Primiceri and Schaumberg (2007) and Justiniano, Primiceri and Tambalotti (2008)). It is interesting to note that this is also the case for the parameter that governs the price rigidity, ξ , despite the fact that the models estimated in the literature include wage (in addition to price) rigidities while our model does not.

To get a sense of how well our model capture the data, Table 4 present the standard deviations of several select variables. Overall, our model of endogenous adoption is in line with data. It slightly underpredicts the variance of output growth and consumption growth and overpredicts the variance of growth in equipment investment and hours growth. These deviations, however, are not remarkable.

To assess how important the innovation shock is as a business cycle driving force, Table 5A and 5B report the contribution of each shock to the unconditional variance of five observable variables: output, consumption and equipment and structures investment and hours worked. We explore the variance decomposition both for the growth rate (Table 5A) and the HP filtered level (Table 5B). We refer to the disturbance to the growth rate of potential new intermediate goods (the "news" shock) as the "innovation" shock.

Our innovation shock accounts for 27 percent of output growth fluctuations and 32 in HP filtered output. It is of nearly equal importance to the neutral technology shock, which accounts 43 percent of fluctuations in output growth and 34 percent in HP filtered output. Investment shocks combined, however, account for more the half the high frequency variation in output, in keeping with the findings of Justiano, Primiceri and Tambalotti (2008). The difference in our model is that we disentangle shocks to equipment versus non-equipment investment and also endogenize the pace of technological change. The shock to non-equipment investment is the third most important explaining approximately 11 percent of output growth fluctuations and 25 percent of HP filtered output. The other 4 shocks seem much less important in explaining output fluctuations explaining a combined 20 percent of output growth fluctuations and less than 9 percent of HP filtered output.

Next we analyze the impulse responses to our innovation/news shock using the estimated model. Figure 3 presents the results. The qualitative patterns are very similar to what we obtained from the calibrated model. In response to a positive news shocks there is a positive and prolonged response of output, investment, consumption and hours worked. The response of output and investment in the estimated model, however, is humped-shaped, reflecting the

various real frictions such as investment adjustment costs that are now present. The response of hours relative to output, however, is somewhat weaker. The introduction of the various frictions has likely dampened the overall hours response. This is somewhat mitigated in conventional models by incorporating wage rigidity.

As in the calibration exercise conducted in section 4, the speed of adoption strongly reacts to the arrival of news about future technology. In Figure 4, we see that in response to the shock, the value of new adopted technologies increases. This is what drives the acceleration in the speed of technology adoption. But not only the value of adopted technologies increases. Also, the prospect of higher future profits also leads to an increase in the value of existing intermediate goods that have not yet been adopted. Finally, the larger flow of intermediate goods that will arrive in the future and the prospects of higher profits also increases the current market value of future intermediate goods. The increases in the market value of the claims to these three types of intermediate goods in response to the news shock explains the stock market boom in Figure 4. Note that this occurs despite the decline in the value of installed physical capital driven by the decline in the relative price of capital. As in the calibrated exercise, the response of the relative price of capital reflects the increase efficiency in the production of new capital due to entry first and more adopted intermediate capital goods later on.

One may wonder whether the monetary policy rule may be playing a role in propagating our news shock by being overly accomodating. We have explored this possibility by shutting off the price rigidity in the model and instead allowing prices to be perfectly flexible. In the process, we have kept the estimated structural parameters from the full blown model. When conducting this exercise, we find that the results for the sticky and flexible price models are very similar. The responses of output and hours are only slightly more dampened in the flexible price model. Thus within our framework, the monetary policy rule has only a small impact of the dynamic response of the model economy to an innovation shock.

The estimated model not only delivers plausible responses to the innovation shock but also to the other shocks considered in the estimation. Figures 5 through 8 report the impulse response functions of our model to the structures price shock and to the neutral technology shock (solid lines). To save space we just report the responses to the other two important shocks though the conclusions qualitatively similar. As with a positive news shock, a positive shock to TFP or a negative shock to the relative price of structures leads to an increase in output, hours, investment, adoption expenses and the stock market. In response to a TFP shock consumption experiences a very small decline due to the large substitution effect introduced by technology adoption and entry. For the shock to the price of structures, instead, consumption is pro-cyclical.

In Figures 5 through 8 we also report (in dashed lines) the impulse responses of a version of our model with exogenous adoption (i.e. constant λ^s , for $s = \{k, y\}$). The main lesson from comparing the responses with endogenous and exogenous adoption is that adoption greatly amplifies not only the effect of the news shock but also the effect of the rest of the shocks in the economy.

Next we conduct a historical decomposition of the data. Figure 9 plots the implied growth rate of new intermediate goods, χ_t . Interestingly, the shock series is highly cyclical and correlated with NBER business cycle peaks and troughs. In addition, the medium frequency component suggests high relative growth of this shock from the mid 1990s to the early 2000s, the time in which the anecdotal evidence suggests a boom in venture capital to finance the development of new technologies linked to the internet. It also drops sharply around 2002, a period where investor expectations clearly turned pessimistic. Figure 10 plots the series for output growth induced by our news shocks together with the actual output growth series. There we can see that the shock also contributes significantly to cyclical output growth. In particular, the shock seems to play a prominent role in recessions and early stages of expansion. Somewhat surprisingly in light of the variance decomposition and of Figure 9, the shock does not seem to be central in the late 1990s boom. Here we suspect that the absence of wage rigidity in our model might be playing a role. As we noted earlier, flexible wages mute the effect of investment shocks on hours.

Finally, we complete our analysis of the model by exploring the evolution of the stock market in the model and in the data. To this end, we take the time series estimated the six shocks and compute the time series for the stock market (Q_t) from the model. Since the data corresponds to the sample of publicly-traded companies and we do not know the share of the total market value that these represent, we normalize the initial level of our predicted series to match the actual value of the stock market.

Figure 11 plots the evolution of the predicted and actual (real) value of the stock market. The actual value is the value of all publicly-traded companies plus the value of their corporate debt. The predicted series tracks fairly closely the actual series for the stock market value. In particular, the model captures the relatively slow growth between 1984 and 1994, the acceleration between 94-95. The peak takes place in 2001 rather than in 2000. Then there is a small decline though not nearly as pronounced as in the 2001 crash. Finally, the model also captures the recovery until the end of 2006.

Beyond the qualitative patterns, the model does a surprisingly good job in capturing the magnitude of the run up during the second half of the 90s. While the US stock market went from a value of \$3.55 trillion in 1984:⁷ to \$24 trillion in 2000:I, our model predicts an increase from \$3.55 trillion to \$21.3 trillion in 2001:I. The similarity of these increases seems remarkable to us given that we have not used any information from the stock market to calibrate or estimate the model.

8 Conclusions

The process by which agents invest in adopting new technologies is key towards understanding business fluctuations. This paper provides several rationales for this claim. Once endogenous technology adoption (and entry) are incorporated

⁷All these figures are in 2000 US dollars.

to an otherwise standard model, news about future technology generate booms in output employment and investment. Further, the process of technology adoption amplifies the effect on the economy of standard macro shocks.

Recognizing that technologies (both adopted and non-adopted) have a value which is (partially) captured by the stock market, it is not only possible but natural to reconcile a counter-cyclical relative price of capital and a pro-cyclical stock market. Our model with endogenous adoption accounts for the volatility of the stock market, its lead over output and the mean reversion of the price-dividend ratio. Further, when shocking our model economy with the shocks estimated to match standard macro variables, we are able to reproduce quite accurately the evolution of the stock market in the last 25 years.

References

- [1] TO BE ADDED

Table1: Calibrated parameters

Parameter	Value
β	0.98
δ	0.015
G/Y	0.2
α	0.35
α_s	0.17/0.35
ζ	1
θ	0.7
$\bar{\lambda}_y$	so that growth rate of $y=0.024/4$
$\bar{\lambda}_k$	so that growth rate of $p_{et}^K=-0.035/4$
U	0.8
$(\delta''/\delta')U$	0.15
ϕ	0.99
μ	1.1
μ_w	1.2
μ_k	1.15
$\bar{\lambda}^y$	so that $\lambda^y=0.02/4$
$\bar{\lambda}^k$	so that $\lambda^k=0.02/4$
ρ_λ	0.9
y	0.7
y_z	0.8
ξ_y	0.6

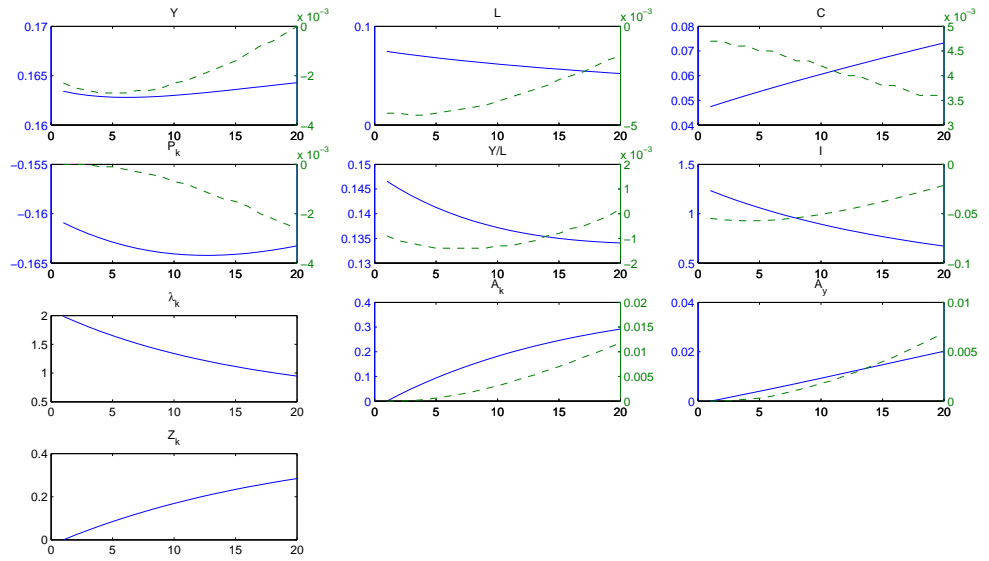


Figure 1: Calibrated response to an innovation shock: endogenous adoption (solid line, left axis), benchmark(dashed line, right axis)

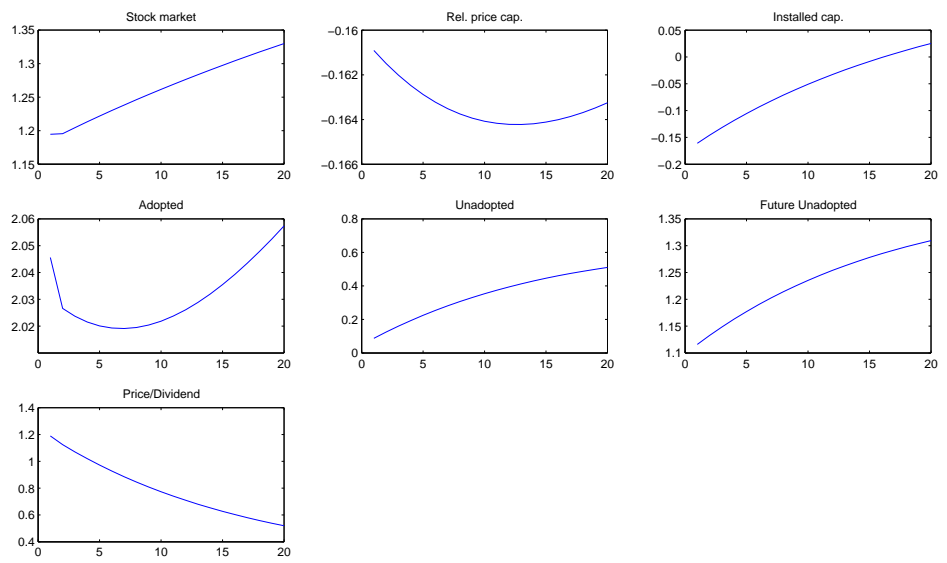


Figure 2: Calibrated stock market and relative price of capital response to an innovation shock

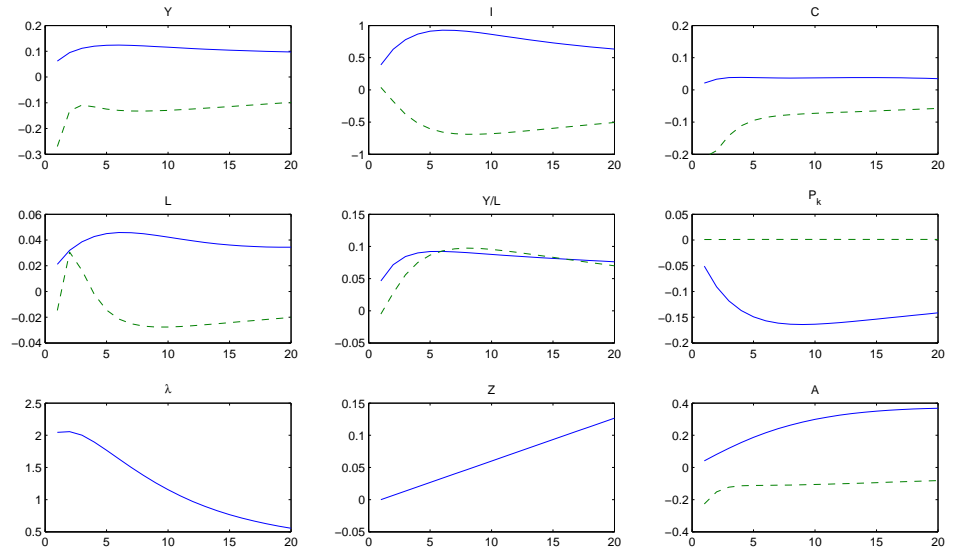


Figure 3: Estimated response to an innovation shock: endogenous adoption (solid line), benchmark(dashed line)

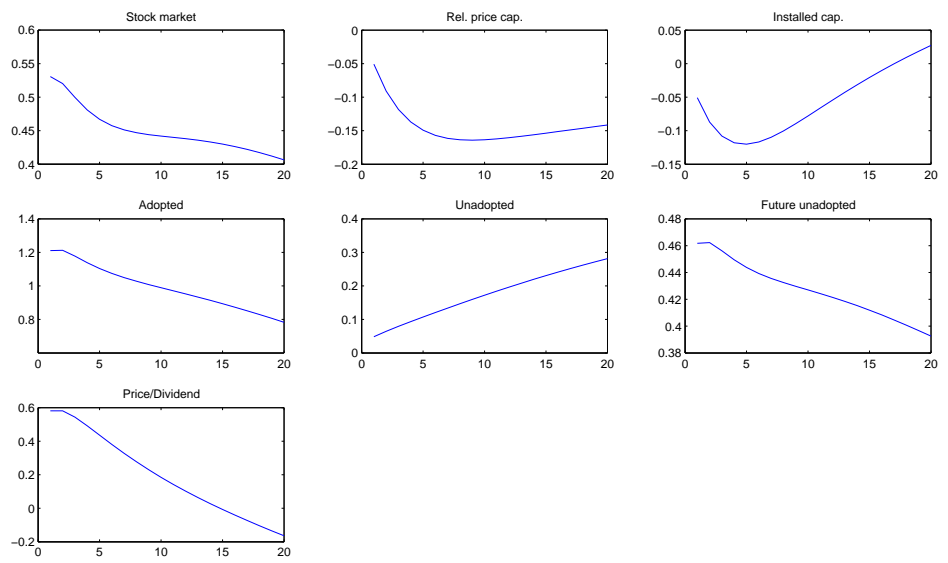


Figure 4: Estimated stock market and relative price of capital response to an innovation shock

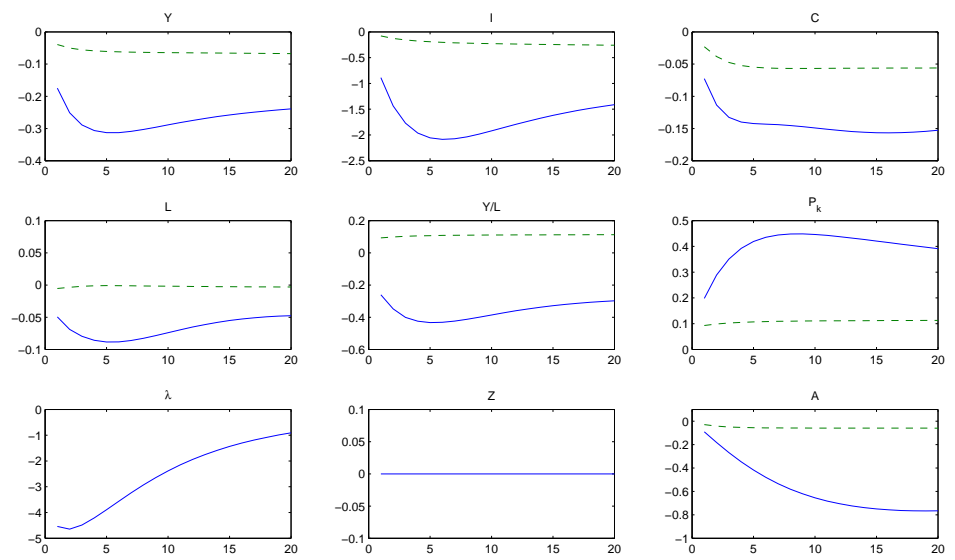


Figure 5: Estimated response to an investment shock: endogenous adoption (solid line), benchmark(dashed line)

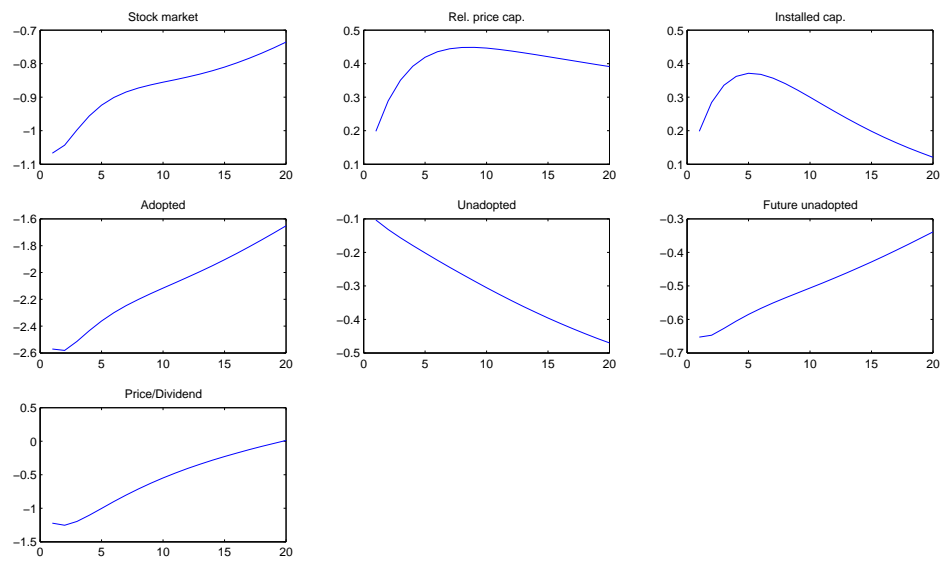


Figure 6: Estimated stock market and relative price of capital response to an investment shock

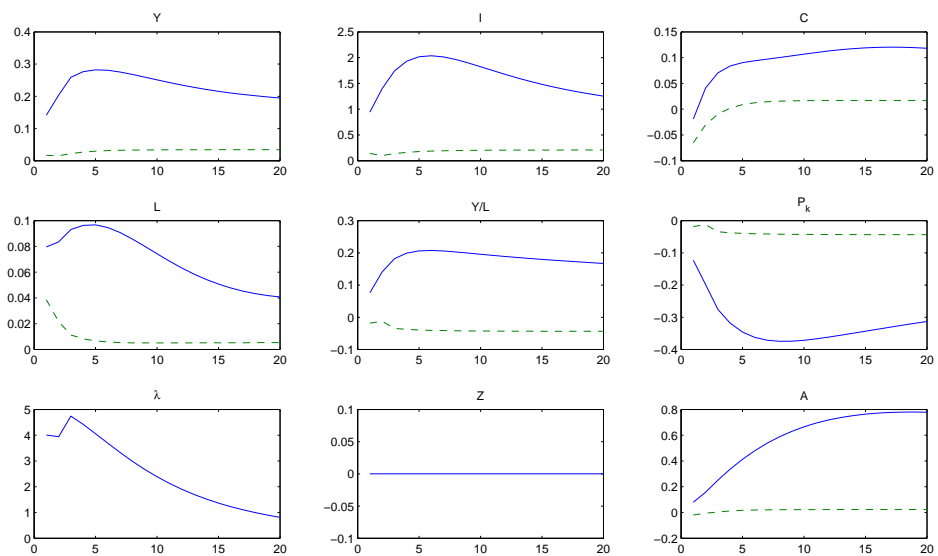


Figure 7: Estimated response to a TFP shock: endogenous adoption (solid line), benchmark(dashed line)

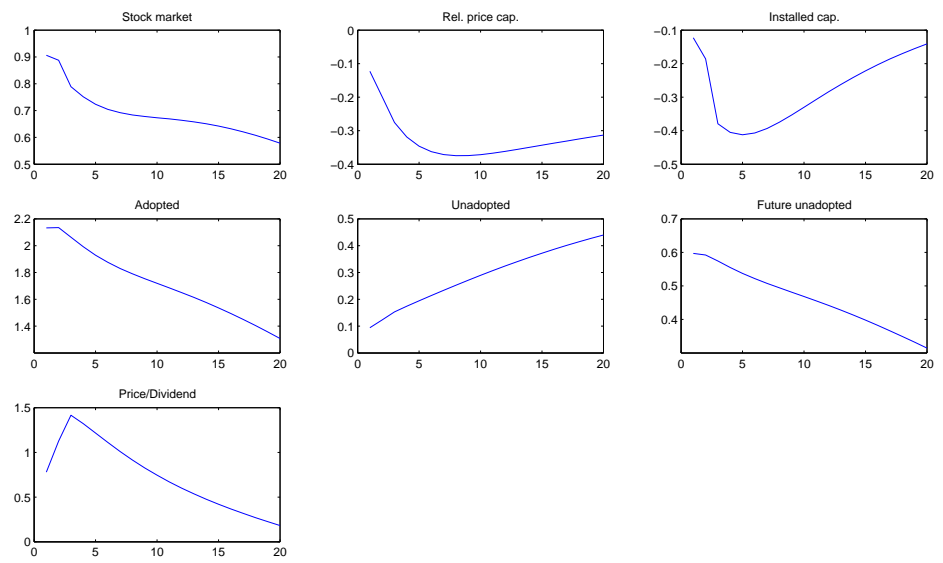


Figure 8: Estimated stock market and relative price of capital response to a TFP shock

Table2: Prior and Posterior Estimates of Structural Coefficients

Parameter	Prior	Posterior			
	Distribution	max	mean	5%	95%
v	Beta (0.50,0.10)	0.502	0.565	0.104	0.952
ρ_r	Beta (0.65,0.10)	0.642	0.623	0.518	0.800
ξ	Beta (0.5,0.10)	0.565	0.557	0.366	0.758
ι_p	Beta (0.5,0.10)	0.488	0.487	0.280	0.694
ψ	Normal (1.00,0.50)	1.305	1.185	0.818	1.510
ϕ_p	Gamma (1.70,0.30)	1.707	1.944	1.226	2.746
ϕ_y	Gamma(0.125,0.10)	0.079	0.082	0.062	0.106
ζ	Gamma (1.20,0.10)	1.193	1.344	1.150	1.516
$\frac{\delta''U}{\delta\tau}$	Gamma (0.10,0.10)	0.025	0.022	0.003	0.043

Table 3: Prior and Posterior Estimates of Shock Processes

Coefficient	Prior	Posterior			
	Distribution	max	mean	5%	95%
ρ_b	Beta (0.25,0.05)	0.235	0.230	0.185	0.284
ρ_m	Beta (0.25,0.05)	0.248	0.247	0.186	0.301
ρ_w	Beta (0.35,0.10)	0.346	0.349	0.331	0.364
ρ_{rd}	Beta (0.95,0.15)	1.000	0.999	0.999	0.999
ρ_g	Beta (0.6,0.15)	0.349	0.894	0.893	0.894
ρ_s	Beta (0.95,0.15)	1.000	0.999	0.999	0.999
σ_{rd}	IGamma(0.25, ∞)	0.285	0.292	0.255	0.337
σ_w	IGamma (0.25, ∞)	0.254	0.263	0.254	0.272
σ_g	IGamma (0.25, ∞)	0.252	0.267	0.248	0.287
σ_b	IGamma (0.25, ∞)	0.252	0.261	0.227	0.296
σ_m	IGamma (0.25, ∞)	0.251	0.268	0.191	0.352
σ_x	IGamma (0.25, ∞)	0.253	0.277	0.269	0.287
σ_s	IGamma (0.25, ∞)	0.306	0.206	0.164	0.245

Table 4: Standard deviations in data and model

Observable	Predicted	Data
ΔY_t	0.50	0.63
ΔI_t^e	2.92	2.23
ΔI_t^s	2.80	2.70
ΔC_t	0.33	0.43
ΔL_t	0.66	0.60

Table 5A: Variance Decomposition

Observable	Gov.	Lab. Supp.	Inter. Pref.	Innov.	Neutr. Tech.	Inves.	Monet. Pol.
ΔY_t	3.45	0.38	9.94	27.15	42.57	10.62	5.89
ΔI_t^e	0.07	0.08	0.74	49.36	35.15	13.67	0.93
ΔI_t^s	0.08	0.09	0.83	33.53	42.05	22.13	1.29
ΔC_t	0.16	1.70	19.38	18.05	40.03	9.43	11.25
ΔL_t	1.61	32.34	0.99	13.69	49.04	1.64	0.69

Table 5B: Variance Decomposition (HP Filtered)

Observable	Gov.	Lab. Supp.	Inter. Pref.	Innov.	Neutr. Tech.	Inves.	Monet. Pol.
Y_t	1.45	0.21	3.84	32.29	34.24	24.78	3.19
I_t^e	0.07	0.06	0.62	35.52	38.00	24.03	1.71
I_t^s	0.08	0.07	0.72	36.92	39.93	20.64	1.65
C_t	0.31	3.61	16.91	15.93	25.60	24.31	13.33
L_t	2.09	35.87	0.75	20.06	29.16	11.24	0.84

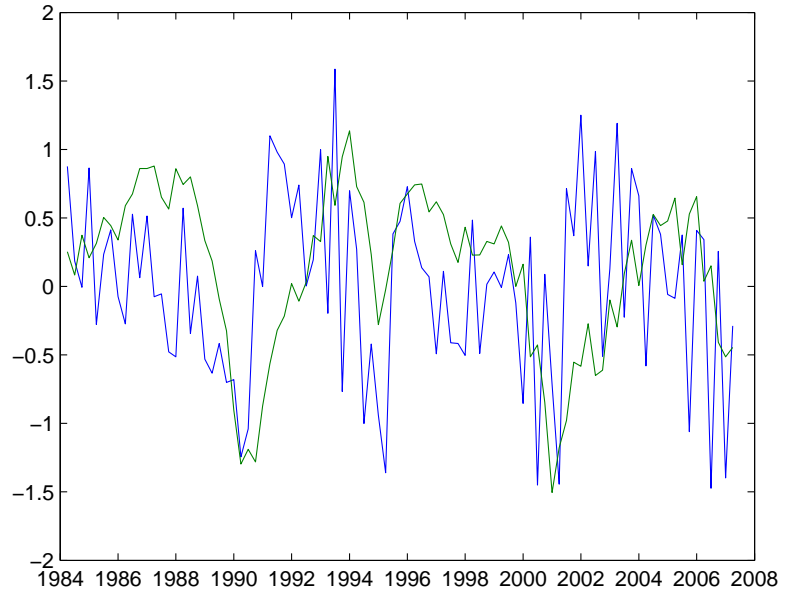


Figure 9: Historical Decomposition Output Growth: green data, blue counterfactual (Innovation Shock)

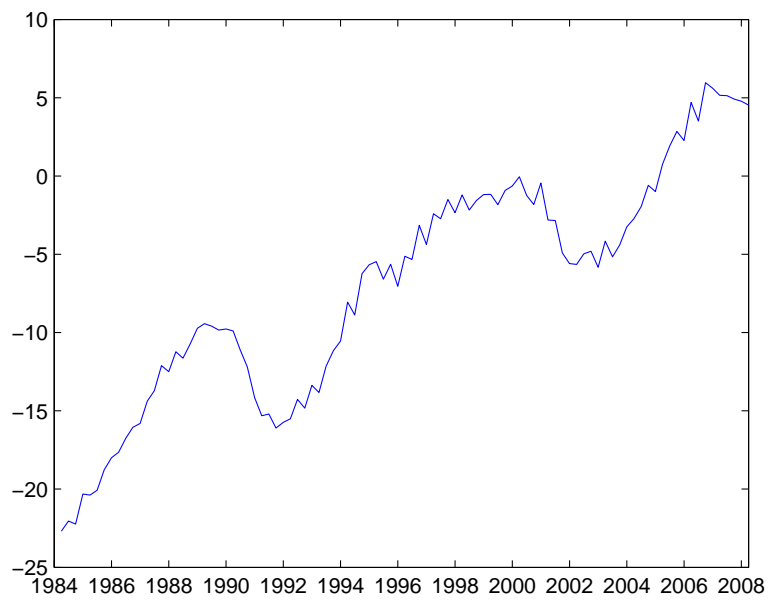


Figure 10: Growth Rate Innovation Shock

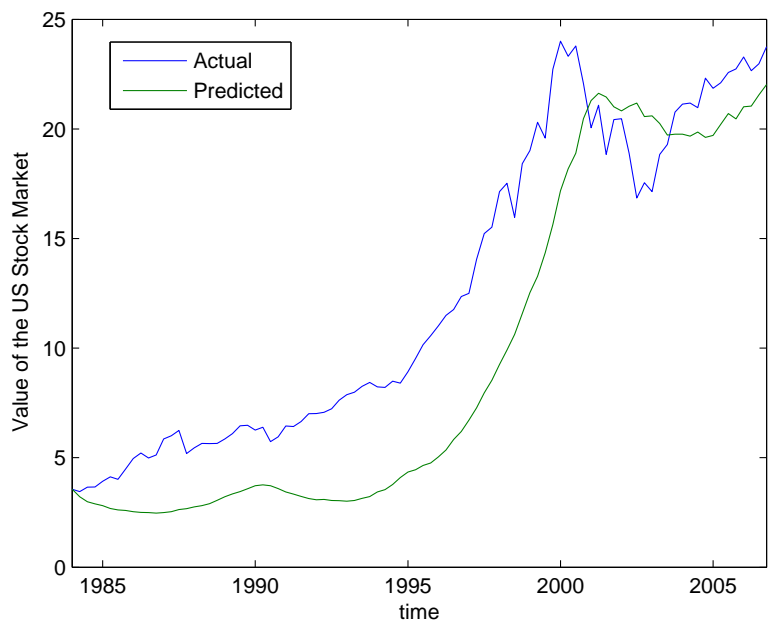


Figure 11: Stock market