

**€ABCN**

**Euro Area Business Cycle Network**



**CENTRE DE RECERCA**

**EN ECONOMIA INTERNACIONAL**

**GENERALITAT DE CATALUNYA**

**UNIVERSITAT POMPEU FABRA**

## **Euro Area Business Cycle Network**

# **Business Cycle Developments, Financial Fragility, Housing and Commodity Prices**

CREI (Universitat Pompeu Fabra), Barcelona

21-23 November 2008

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

\*Diego Comin (Harvard), Mark Gertler (NYU) and Ana Maria Santacreu (NYU)

We are grateful to the following institutions for their financial and organisational support: CREI and the Euro Area Business Cycle Network.  
The views expressed in this paper are those of the author(s) and not those of the funding organization(s), which takes no institutional policy positions.

# Changes in Growth Potential and Endogenous Technology Diffusion as Sources of Output and Asset Price Fluctuations

Diego Comin, Mark Gertler and Ana Maria Santacreu\*

November, 2008

## 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 gyrations in stock prices over this period. Finally, the endogenous adoption mechanism plays a significant 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 key factor in some of the postwar recessions, including the current one, but not in all.

---

\*We appreciate the helpful comments of Bob King, Marianne Baxter and seminar participants at the Boston Fed, Brown, Boston University and the University of Valencia. Financial assistance from the C.V. Starr Center and the NSF is greatly appreciated.

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 its 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, 2003). 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.

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, Ilut, Motto and Rostagno (2007) 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 leads to a shift in labor demand when the news about future technology arrives. 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, with 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.

In addition, the endogenous diffusion mechanism also works to amplify and propagate other conventional disturbances to the economy, such as exogenous movements in total factor productivity or shocks to the cost of capital investments. Thus the mechanism we develop is potentially also relevant to business fluctuations driven primarily by factors other than news about future prospects. It generates an endogenous link between the business cycle and an economy's growth prospects over the medium term.

The framework also broadly captures the cyclical pattern of stock price movements. Conventional models have problems generating large procyclical movements in stock prices. In these models the value of the firm is the value of installed capital. One immediate problem is that, 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.

Unlike with standard macro models, in our framework firms have the rights to the profit flow of current and future adopted technologies, in addition to the value of installed capital. 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 the earnings from projects that are productive only when they are adopted in the future, the price-earnings ratio is highly mean reverting, as is consistent with the evidence.

Before proceeding we should emphasize that 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 endogenous technology adoption mechanism and our news shock as a prelude to an estimated model that we present in section 5. 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 3 and 4 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.

In section 5, 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. Section 6 reports the estimates for a sample period covering 1984:1 to 2008:2. Overall, we show that the main findings from the calibrated model are robust to an estimated mode that provides a reasonable fit of the data. In addition, our "news/innovation" shock is an important driver of business fluctuations. In particular, it explains 27 percent of output growth (32 percent of HP filtered output).

In section we analyze the implications for the stock market. We show that, broadly speaking, the model captures the overall volatility of stock prices, as well as the co-movement with output. Somewhat surprisingly, it can account for the run-up of stock prices in the mid 1990s. Finally, by running the model through "Campbell-Shiller" tests, we show the model can capture the kind of stock-price/earnings dynamics observed in the data.

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 shocks 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  $\delta_t$  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 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  $r^{\text{th}}$  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  $s^{\text{th}}$  intermediate capital good as a fixed markup  $\theta$  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  $\varepsilon_{st}$  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  $\mu$  is inversely related to the price elasticity of substitution across goods.

Let  $Y_t(j)$  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  $\varsigma_t$  is first order serially correlated innovation.<sup>1</sup>

Following Greenwood, Hercowitz and Huffman (1988), we further assume that a higher rate of capital utilization comes at the cost of a faster depreciation

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

rate,  $\delta$ . 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 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.<sup>2</sup> 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:

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

---

<sup>2</sup>An 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.

where  $\phi$  is the fraction of intermediate goods that do not become obsolete, and  $\chi_t$  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  $\varepsilon_t$  is a white noise disturbance. In addition, we normalize the elasticity of new technologies with respect to the innovation shock in the capital sector  $\xi_k$  at unity. Though we allow  $\xi_y$  to differ from unity.

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  $\xi_s$ , 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 in capture by innovations in  $\chi_t$ , 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  $\lambda_t^s$ , 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,<sup>3</sup> we will obtain a pro-cyclical adoption behavior by endogenizing the probability  $\lambda_t^s$  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  $\lambda_t^s$  is increasing in adoption expenditures, follows:

---

<sup>3</sup>Comin (2007).

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

with  $\lambda' > 0$ ,  $\lambda'' < 0$ , where  $h_t^s$  are the resources devoted to adopting one technology in time  $t$  and where  $\Gamma_t$  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 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  $\pi_t^s$  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  $\Pi_t$  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

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

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

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

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

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

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  $P_t^K$ .

As mentioned in the introduction, in standard macro models, the market value of corporations is equal to the value of installed capital. This creates a serious challenge for these models. Since capital is a stock, the short run evolution of this first term is driven by the dynamics of the price of capital. In the data, the relative price of capital is countercyclical and moves about as much as output. The stock market, however, is strongly pro-cyclical and moves about ten times more than output. A theory that equalizes the two variables will have to be inconsistent with the empirical behavior of at least one of the two.

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

$$Q_t = \overbrace{P_t^k K_t}^{\text{Replacement value of capital}} + \sum_{s=\{k,y\}} \overbrace{A_t^s (v_t^s - \pi_t^s)}^{\text{Value of adopted technologies}} \quad (23)$$

$$+ \sum_{s=\{k,y\}} \overbrace{(j_t^s + h_t^s)(Z_t^s - A_t^s)}^{\text{Value of existing not adopted technologies}} + E_t \left[ \sum_{s=\{k,y\}} \overbrace{\sum_{i=0}^{\infty} \beta \Lambda_{t,t+1+i} j_{t+1+i}^s (Z_{t+1+i}^s - \phi Z_{\tau+i}^s)}^{\text{Value of future non-adopted technologies}} \right]$$

First, the market values the capital stock installed in firms. This is captured by the first term. As we have argued above, our model predicts that 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.

Unlike the replacement value of capital, the three terms that capture the discounted value of profits of current and future intermediate goods are highly pro-cyclical. As we shall see, their response to the standard shocks dominates the response of the price of capital and, as a result, the stock market will be pro-cyclical.

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. Table 1 reports the value for these parameters.

We begin with the standard parameters. A period in our model corresponds to a quarter. We set the discount factor  $\beta$  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)  $U = 0.8$ .<sup>4</sup> We set the inverse of the Frisch elasticity of labor supply  $\zeta$  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 to 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,  $\mu$ , equal to 1.1 and the corresponding markup for the capital goods sector,  $\mu^k$ , 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 ( $\theta$ ) and output goods ( $\vartheta$ ) to 1.4 and 1.25, respectively. Following Caballero and Jaffe (1992), we set  $\phi$  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  $\theta$ , the obsolescence rate and  $\xi_k$ . We normalize  $\xi_k$  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.

$\xi_y$  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  $\chi_t$ , the variance of  $x_t$  and  $\xi_y$ . Hence, we can use these three moments in the data to identify  $\xi_y$ . This yields an estimate for  $\xi_y$  of approximately 0.6. Our results are quite robust to variation in  $\xi_y$  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  $\chi_t$ .

We now consider the parameters that govern the adoption process. We use two parameters to parameterize the function  $\lambda^s(\cdot)$  as follows:

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

---

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

These are  $\bar{\lambda}^s$  and  $\rho_\lambda$ . 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 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.<sup>5</sup> For these reasons, we set  $\bar{\lambda}^s$  to match an average adoption lag of 5 years and a quarter.<sup>6</sup>

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  $s = \{k, y\}$ .

The main observation is that, while the positive news about future technology leads 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

---

<sup>5</sup>Comin and Hobijn (2007) and Comin, Hobijn and Rovito (2008).

<sup>6</sup>It 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 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.

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  $\lambda_t$ .

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,  $\chi_t$ , 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. This increases current output and allows also consumption to increase once the news shock hits the economy. In the Appendix, we illustrate this point with the response of the economy to a news shock once the entry mechanism is shut down. In this case, hours, investment and output respond positively to a news shock, but consumption initially declines.

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 An Extended Model for 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.

### 5.1 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  $\mu_t^w$  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  $\gamma$ , 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 Schaumberg (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  $\xi$  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  $\Pi$  and  $\iota_p$  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.

## 6 Estimation

### 6.1 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 de-mean 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.

Final, 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 (2007) 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.

## 6.2 Priors and Posterior Estimates and Model Fit

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,  $\xi$ , 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 presents 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.

Finally, we note that our model provides a reasonable fit of the data, at least as compared to reasonable competing alternatives. Table 6 shows that the marginal likelihood for our baseline model is significantly higher than an alternative formulation with exogenous as opposed to endogenous adoption. Both models are preferred to a version with a conventional real and monetary sector, similar to Justiniano, Primiceri and Tambalotti (2008), though without wage rigidity (in order to be comparable to our specification.)

### 6.3 Estimated Impulse Response Functions

Next we analyze the impulse responses to our innovation/news shock using the estimated model. Figure 2 presents the results for our model (solid line) and for the version with exogenous adoption (dashed line). 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.<sup>7</sup> 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.

The speed of adoption strongly reacts to the arrival of news about future technology. In Figure 3 (first panel in second row), 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. Further, it is critical to understand the fluctuations in the stock market.

Recall from equation (23) in section 3 that, unlike standard macro models, in our framework the firm has the rights to the profit flow of current and future adopted technologies. Thus, the market value of companies is given by the present discounted value of profits from current and future intermediate goods in addition to the value of installed capital. But, in response to a news shock, 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 (Figure 3, second panel in second row).

---

<sup>7</sup>As in the calibrated model, a positive news shock generates a recession rather than a boom.

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 (Figure 3, third panel in second row).

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 3, first panel in the first row. 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 increased efficiency in the production of new capital due to entry, first, and more adopted intermediate capital goods later on.

As in the data (e.g. Comin and Gertler, 2006), the relative price of capital moves roughly as much as output in response to the news shock. The stock market, however, moves much more than output. The news shock drives fluctuations in the stock market that are about ten times larger than in the data which is also consistent with the empirical evidence for the US.

There are other interesting observations from figure 3. First, the stock market leads output. Intuitively, this is the case because the stock market incorporates the value of future profits which strongly co-move with future 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 response of output and dividends, instead, is more muted and increasing over time. As a result, the price-dividend ratio is mean reverting (Figure 3, first panel third row) which is consistent with the evidence (REF).

Finally, one by-product of this is that the model is consistent with the finding by Beaudry and Portier that stock prices uncorrelated with current total factor productivity help predict future productivity. Intuitively, the response of TFP to a news shock mimics the response of output. Since the stock market leads output, our model predicts that current increases in the stock market orthogonal to the increase in output will predict future output, and, hence, future TFP.

One may wonder whether the monetary policy rule may be playing a role in propagating our news shock by being overly accommodating. 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 4 through 7 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, initially, experiences a very small decline due to the large substitution effect introduced by technology adoption and entry. After, that, consumption increases. For the shock to the price of structures, instead, consumption is pro-cyclical. It is also worth noting that, because these shocks induce pro-cyclical fluctuations in the value of adopted technologies, they also generate large, pro-cyclical fluctuations in the speed of adoption of new technologies.

In Figures 4 through 7 we also report (in dashed lines) the impulse responses of a version of our model with exogenous adoption (i.e. constant  $\lambda^s$ , 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.

In Figures 5 and 7 we plot the responses of the stock market, its components, the relative price of capital and the price-dividend ratio to the investment price and TFP shocks, respectively. The main observation is that the response of these variables to these shocks are very similar to their responses to the news shock. In particular, the stock market is highly pro-cyclical while the relative price of capital is counter-cyclical. Both of them move (relative to output) by approximately the same magnitudes as observed in the data. The stock market leads output, its fluctuations are persistent and mean reverting. As well as the price-dividend ratio. Further, it seems that the responses of output and the stock market to shocks other than news shocks, such as TFP and the price of investment, are also consistent with the finding by Beaudry and Portier that stock prices uncorrelated with current total factor productivity help predict future productivity. This means that, in models with endogenous adoption, the Beaudry-Portier finding does not say much about the importance of news shocks in fluctuations.

## 6.4 Historical Decompositions

Next we conduct a historical decomposition of the data. Figure 9 plots the implied growth rate of new intermediate goods,  $\chi_t$ . 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 8 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 8, 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.

## 7 A Closer Examination of the Stock Market: Model vs. Data

In this section we examine in greater detail the ability of our model to account for stock prices models. We take up two issues: first, whether the model can account for the dramatic swings in stock prices over the sample; second, whether it is consistent with the Campbell-Shiller (1988) evidence that price/dividend ratios are driven mainly by movements in risk premia, something from which we abstract in our analysis.

To compare the evolution of the stock market in the model and in the data, 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 the share of the total market value that these companies represent is not directly measurable, we normalize the initial level of our predicted series to match the actual value of the stock market.<sup>8</sup>

Figure 10 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. The model also captures the recovery until the end of 2007. Finally, it captures the decline in the stock market in 2008 through the second quarter, though in the model it starts in 2007. Unfortunately, we cannot compare this to actual data because we do not have the series on corporate debt for 2007 and 2008. However, the decline in stock prices in the first half of 2008 is strong enough for the value of the stock market to be qualitatively consistent with the model predictions for the end of the sample period. To be sure, we make no claim that our model can account for the sharp contraction in stock prices, beginning in October 2008 since we have abstract from financial factors that appear to be relevant to this phenomenon.

---

<sup>8</sup>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 the 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 cyclicalities 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.

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:I<sup>9</sup> 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 striking to us given that we have not used any information from the stock market to estimate the model.

We now turn to the Campbell-Shiller (1988) evidence. We proceed by generate artificial data from the model and then running this data through the battery of tests that the authors perform. To begin, Table X presents a comparison of the relevant moments of the stock market variables from the model versus the data.. In the top panel we report some univariate moments for the growth rate of nominal dividends, the growth rate of nominal stock prices and the price dividend ratio. The only reason we use nominal rather than real variables is to follow Campbell and Shiller (1988), which becomes very relevant in the bottom panel of Table X.<sup>10</sup> The period we study is 1984-2006. Columns I and III report the standard deviation of the relevant variables in the data and in the model, respectively. Columns II and IV report the first order autocorrelations in the data and model, respectively. Column V reports the p-value of the Wald test of the null that the standard deviation is the same in the data and in the model. Column VI reports a similar statistic for the autocorrelation.

Overall, the model data is a reasonable characterization of the actual data. It is true that dividend growth is more volatile in the data than in the model. But this to a large part may be because the distributions measure used by Campbell and Shiller does not include interest payments on debt, in contrast to our measure, which reflects total payouts to capital. A related observation is that dividend growth is more persistent in the model than in the data. However, this difference is not statistically significant at the 1% level. The model and the data exhibit similar volatility of stock price growth. While stock price growth is more persistent in the model, the difference is not statistically significant at conventional levels.

Since dividends are more volatile in the data than in the model, and dividends and stock prices are positively correlated, the price dividend ratio is more volatile in the model than in the data. This difference, though, is not statistically significant. Finally, the persistence of the price dividend ratio is similar in the model and the data.

We now perform the basic Campbell and Shiller (1988) exercise on our data.. In their paper, Campbell and Shiller investigate whether the standard asset pricing model can account for fluctuations in the price-dividend ratio. Specifically, they approximate the (log) price dividend ratio ( $q_t - d_t$ ) as the following function of expected future dividend growth ( $E_t \Delta d_{t+j}$ ) and expected future discount rates ( $E_t r_{t+j}$ )<sup>11</sup>

---

<sup>9</sup>All these figures are in 2000 US dollars.

<sup>10</sup>The conclusions of the comparison are very similar for real variables.

<sup>11</sup>The term  $c$  is a constant and  $\rho$  is the steady state value of the ratio of the price to the sum of the price and the dividend.

$$q_t - d_t \simeq E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+j} - r_{t+j}) + c \quad (31)$$

where  $c$  is a constant. Then, Campbell and Shiller forecast future discounted dividend growth ( $\Delta d_{t+j} - r_{t+j}$ ) using a linear VAR with two variables, the price-dividend ratio and lagged discounted dividend growth ( $\Delta d_{t+j-1} - r_{t+j-1}$ ).<sup>12</sup> Using these forecasting rules and a calibrated value for  $\rho$ , they the forecasts for the price dividend ratio based on the RHS of (31) and compare them to the actual price-dividend ratios.

Their main findings are that, while the forecast of the price dividend ratio series is highly correlated with the actual price-dividend ratio, its variance is much smaller. This leads them and many others that it must be an unobserved time varying risk premium that accounts for the observed price dividend movements.

One interesting question raised by this exercise is whether the failure to account for fluctuations in the price-dividend ratio is due to an unobserved risk premium or because the forecasts produced by small VARs such as those used by Campbell and Shiller may not accurately forecast future dividend growth. Campbell and Shiller argue that this second avenue to explaining their results is unlikely because they include the price-dividend ratio in their VAR which should incorporate all the information possessed by market participants as of time  $t$ . Their VARs, however, are restricted to linear functions of the included variables and have a small number of lags.

In our model, however, stock market value depends not only on the dividend stream generated by operating assets, but also on the option value of project that have yet to be adopted or created. The link between past dividends and prices and the dividend stream from these potential revenue creating assets may not be easily capture from the simple Campbell/Shiller specification.

To address this issue we update the Campbell and Shiller exercise for our sample period and then do the same with our simulated data.<sup>13,14</sup> For concreteness we restrict ourselves to VARs with only one lag.

The bottom panel of table 7 reports our main findings both for the actual and simulated data. In particular we report the ratio of the standard deviation of the forecasted to standard deviation of the actual price dividend ratio series and the correlation between the two. As Campbell and Shiller, we find that in the more recent period it is both the case that forecasted price dividend ratios are

<sup>12</sup>Campbell and Shiller (1988) experiment with various measures of the real interest rate. These include, three-month T-bills, a linear function of consumption growth and a measure of stock market volatility. The findings are robust to these variations. They also experiment with alternative specifications with three variables separating the effects of dividend growth and discount rates. Their result are also robust to these variations.

<sup>13</sup>In updating Campbell and Shiller (1988) we use the same data sources as they do, in particular we obtain stock price and dividend data from the value weighted stock returns for the NYSE from CRSP with and without distributions. For the discount rates we use three-month T-bills.

<sup>14</sup>The results in the simulated data are robust to using quarterly rather than annual data.

much less volatile than actual price dividend ratios. In our sample, the ratio of the standard deviations is 0.66 while in the earlier period they study this ratio is 0.54. We also find that the two are highly correlated, though the correlation in the 1984-2006 period (0.87) is lower than the correlation in the 1926-1986 period (0.99).

When looking at the price dividend ratio in the simulated data, we find that the forecasted price dividend ratio are also less volatile than the actual price dividend ratios. The ratio is now 0.44 which is slightly smaller than the equivalent ratio for the actual data. For the simulated data, we also find that price dividend ratios are highly correlated to forecasted price dividend ratios, though the correlation is slightly smaller than in the data (0.54 vs. 0.87). Thus, our model predictions are broadly consistent with the findings in Campbell and Shiller (1988). In particular, even though our model does not contain a time varying risk premium, the price dividend ratio the model generates is more volatile than the one implied by expected discounted dividends, based on a simple model for forecasting future dividends.

In particular, since our data has been generated according to our model, we know that our asset-pricing model is consistent with the (simulated) data. Hence, in our case, the failure of the Campbell-Shiller type of forecasts to account for fluctuations in the price-dividend ratio is clearly due to the inability of the VARs to produce good forecasts of future discounted dividend growth. This is not surprising given the relative complexity of our model (and, quite likely, also of the US economy). It contains many state variables, technologies diffuse slowly and non-linearly and future dividends depend, in part, of the process of diffusion of the current unadopted technologies. Therefore, current dividends are not great predictors of future dividends.

## 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 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] An, Sungbae and Frank Schorfheide (2007). "Bayesian Analysis of DSGE Models," *Econometric Reviews* 26, 113-172
- [2] Basu, Susanto and John G. Fernald (1997). "Returns to Scale in U.S. Production: Estimates and Implications," *Journal of Political Economy* 105(2), 249-283
- [3] Beaudry, Paul, Fabrice Collard and Franck Portier (2007). "Gold Rush Fever in Business Cycles," mimeo, University of British Columbia
- [4] Beaudry, Paul and Franck Portier (2004). "An Exploration into Pigou's theory of cycles," *Journal of Monetary Economics* 51, 1183-1216
- [5] Beaudry, Paul and Franck Portier (2006). "News, Stock Prices and Economic Fluctuations," *American Economic Review* 96(4), 1293-1307
- [6] Beveridge, William H. (1909). *Unemployment: A Problem of Industry*, Longmans, Green, and Co.
- [7] Caballero, Ricardo J. and Adam B. Jaffe (1993). "How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth," *NBER Macroeconomics Annual*, O. J. Blanchard and S. Fischer editors, MIT press, 15-72
- [8] Christiano, Lawrence J., Martin Eichenbaum and Charles L. Evans (2005). "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy* 113(1), 1-45
- [9] Christiano, Lawrence J., Cosmin Ilut, Roberto Motto, and Massimo Rostagno (2007). "Monetary Policy and Stock Market Boom-Bust Cycles," mimeo, Northwestern University
- [10] Clark, John M. (1934). *Strategic Factors in Business Cycles*, NBER
- [11] Cochrane, John (1994). "Shocks," *Carnegie-Rochester Conference Series on Public Policy* 41, 295-364
- [12] Comin, Diego (2007). "On the Integration of Growth and Business Cycles," *Empirica* (forthcoming)
- [13] Comin, Diego and Mark Gertler (2006). "Medium-Term Business Cycles," *American Economic Review* 96(3), 523-551
- [14] Comin, Diego and Bart Hobijn (2007). "Lobbies and Technology Diffusion," *Review of Economics and Statistics* (forthcoming)
- [15] Comin, Diego, Bart Hobijn and Emilie Rovito (2008). "A New Approach to Measuring Technology with an Application to the Shape of Diffusion Curves," *Journal of Technology Transfer*(forthcoming)

- [16] Greenwood, Jeremy, Zvi Hercowitz and Gregory W. Huffman (1988). "Investment, Capacity Utilization, and the Real Business Cycle," *The American Economic Review* 78(3), 402-417
- [17] Greenwood, Jeremy, Zvi Hercowitz and Per Krusell (2000). "The role of investment-specific technological change in the business cycle," *European Economic Review* 44(1), 91-115
- [18] Hall, Robert E. (2000). "e-Capital: The Link between the Labor Market and the Stock Market in the 1990s," *Brookings Papers on Economic Activity* 2, 73-118
- [19] Jaimovich, Nir and Sergio Rebelo (2006). "Can News about the Future Drive the Business Cycle?," mimeo, Northwestern University
- [20] Justiniano, Alejandro, Giorgio E. Primiceri and Andrea Tambalotti (2008). "Investment Shocks and Business Cycles," CEPR discussion paper No. 6739
- [21] Mansfield, Edwin (1989). "The diffusion of industrial robots in Japan and the United States," *Research Policy* 18(4), 183-192
- [22] Pigou, Arthur C. (1927). *Industrial Fluctuations*, Macmillan and Co.
- [23] Primiceri, Giorgio E., Ernst Schaumburg and Andrea Tambalotti (2006). "Intertemporal Disturbances," NBER working paper No. 12243
- [24] Smets, Frank and Raf Wouters (2007). "Shocks and Frictions in U.S. Business Cycles: A Bayesian DSGE Approach," *American Economic Review* 97(3), 586-606
- [25] Stock, James H. and Mark W. Watson (2003). "Forecasting Output and Inflation: The Role of Asset Prices," *Journal of Economic Literature*, 41(3), 788-829

## 9 Tables and Figures

Table1: Calibrated parameters

Parameter	Value
$\beta$	0.98
$\delta$	0.015
$G/Y$	0.2
$\alpha$	0.35
$\alpha_s$	0.17/0.35
$\zeta$	1
$\theta$	0.7
$\bar{\chi}_y$	so that growth rate of $y=0.024/4$
$\bar{\chi}_k$	so that growth rate of $p_{et}^K=-0.035/4$
$U$	0.8
$(\delta''/\delta')U$	0.15
$\phi$	0.99
$\mu$	1.1
$\mu_w$	1.2
$\mu_k$	1.15
$\bar{\lambda}^y$	so that $\lambda^y=0.02/4$
$\bar{\lambda}^k$	so that $\lambda^k=0.02/4$
$\rho_\lambda$	0.9
$y$	0.7
$y_z$	0.8
$\xi_y$	0.6

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
$\rho_r$	Beta (0.65,0.10)	0.642	0.623	0.518	0.800
$\xi$	Beta (0.5,0.10)	0.565	0.557	0.366	0.758
$\iota_p$	Beta (0.5,0.10)	0.488	0.487	0.280	0.694
$\psi$	Normal (1.00,0.50)	1.305	1.185	0.818	1.510
$\phi_p$	Gamma (1.70,0.30)	1.707	1.944	1.226	2.746
$\phi_y$	Gamma(0.125,0.10)	0.079	0.082	0.062	0.106
$\zeta$	Gamma (1.20,0.10)	1.193	1.344	1.150	1.516
$\frac{\delta''U}{\delta'}$	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%
$\rho_b$	Beta (0.25 0.05)	0.235	0.230	0.185	0.284
$\rho_m$	Beta (0.25,0.05)	0.248	0.247	0.186	0.301
$\rho_w$	Beta (0.35,0.10)	0.346	0.349	0.331	0.364
$\rho_{rd}$	Beta (0.95,0.15)	1.000	0.999	0.999	0.999
$\rho_g$	Beta (0.6,0.15)	0.349	0.894	0.893	0.894
$\rho_s$	Beta (0.95,0.15)	1.000	0.999	0.999	0.999
$\sigma_{rd}$	IGamma(0.25, $\infty$ )	0.285	0.292	0.255	0.337
$\sigma_w$	IGamma (0.25, $\infty$ )	0.254	0.263	0.254	0.272
$\sigma_g$	IGamma (0.25, $\infty$ )	0.252	0.267	0.248	0.287
$\sigma_b$	IGamma (0.25, $\infty$ )	0.252	0.261	0.227	0.296
$\sigma_m$	IGamma (0.25 $\infty$ )	0.251	0.268	0.191	0.352
$\sigma_x$	IGamma (0.25, $\infty$ )	0.253	0.277	0.269	0.287
$\sigma_s$	IGamma (0.25, $\infty$ )	0.306	0.206	0.164	0.245

Table 4: Standard deviations in data and model

Observable	Predicted	Data
$\Delta Y_t$	0.50	0.63
$\Delta I_t^e$	2.92	2.23
$\Delta I_t^s$	2.80	2.70
$\Delta C_t$	0.33	0.43
$\Delta L_t$	0.66	0.60

Table 5A: Variance Decomposition

Observable	Gov.	Lab. Supp.	Inter. Pref.	Innov.	Neutr. Tech.	Inves.	Monet. Pol.
$\Delta Y_t$	3.45	0.38	9.94	27.15	42.57	10.62	5.89
$\Delta I_t^e$	0.07	0.08	0.74	49.36	35.15	13.67	0.93
$\Delta I_t^s$	0.08	0.09	0.83	33.53	42.05	22.13	1.29
$\Delta C_t$	0.16	1.70	19.38	18.05	40.03	9.43	11.25
$\Delta L_t$	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

Table 6: Log-Marginal Density Comparison

Specification	Log Marginal
Benchmark	1906
Exogenous Adoption	2092
Endogenous Adoption	2337

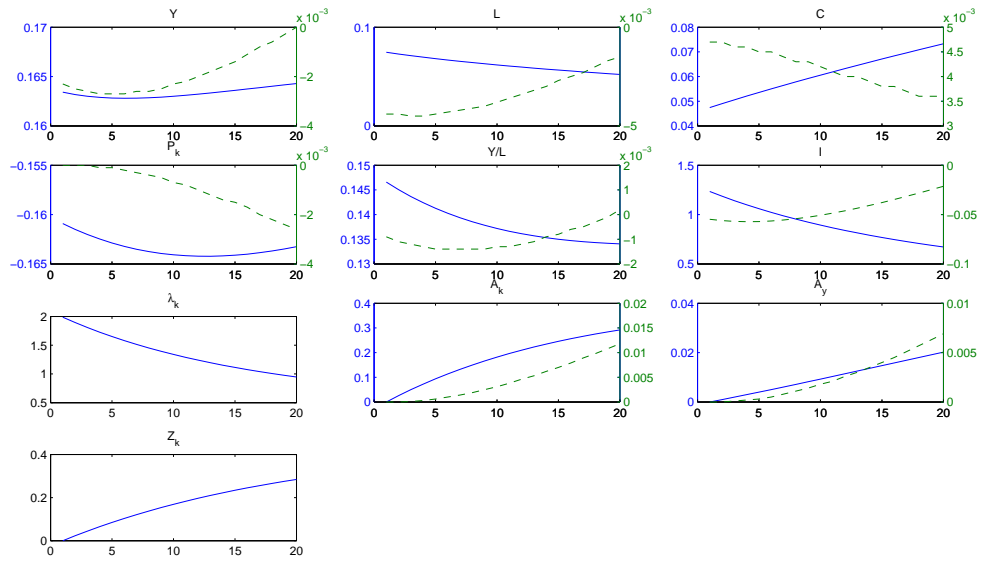


Figure 1: Calibrated response to an innovation shock: endogenous adoption (solid line, left axis), benchmark(dashed line, right axis)

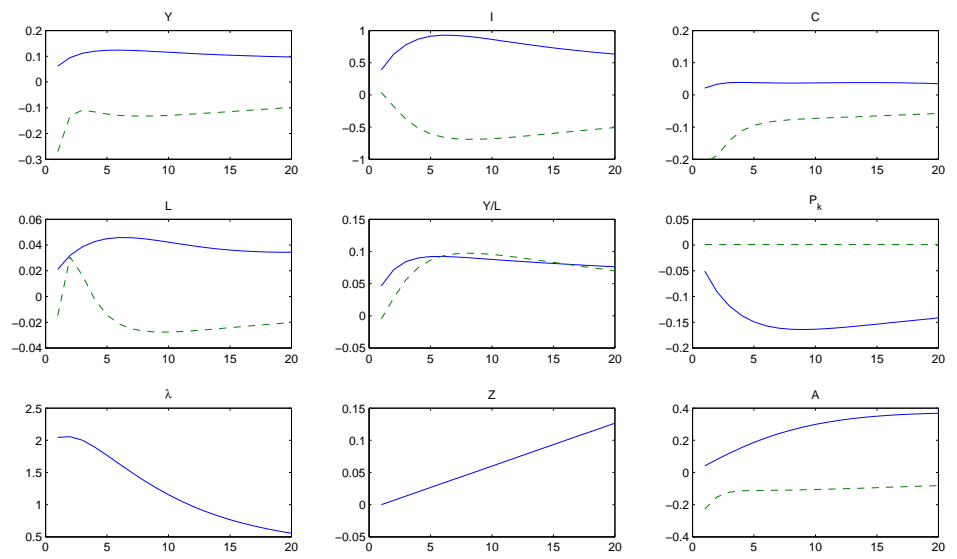


Figure 2: Estimated response to an innovation shock: endogenous adoption (solid line), benchmark(dashed line)

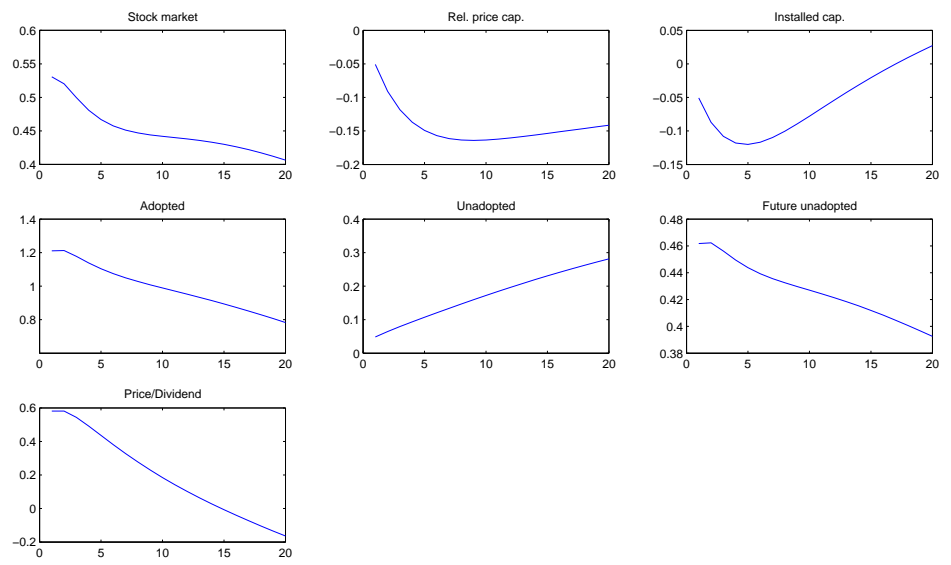


Figure 3: Estimated stock market and relative price of capital response to an innovation shock

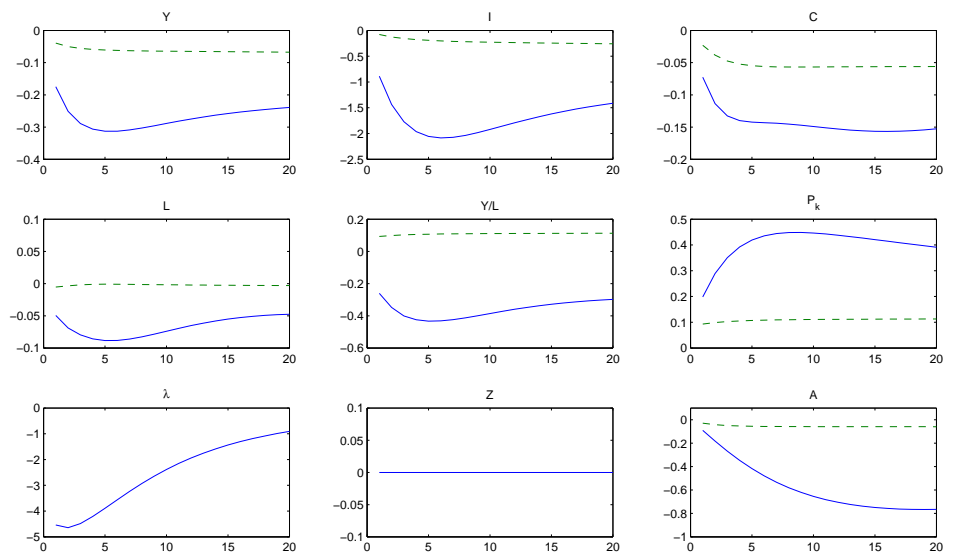


Figure 4: Estimated response to an investment shock: endogenous adoption (solid line), benchmark(dashed line)

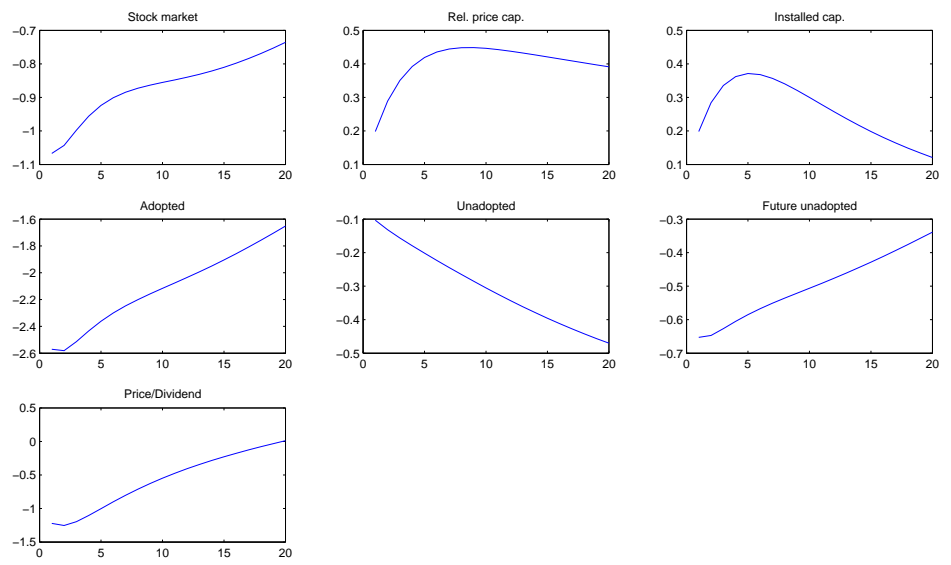


Figure 5: Estimated stock market and relative price of capital response to an investment shock

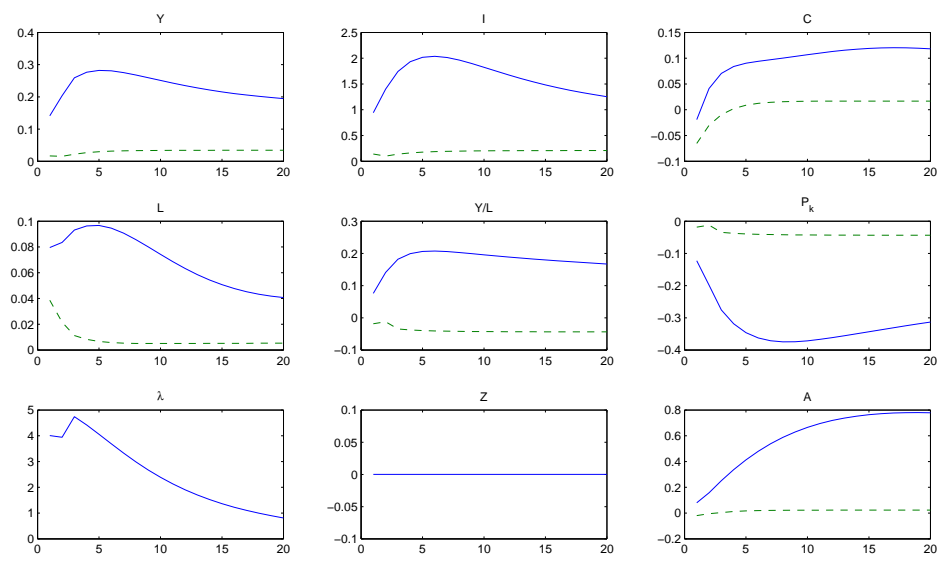


Figure 6: Estimated response to a TFP shock: endogenous adoption (solid line), benchmark(dashed line)

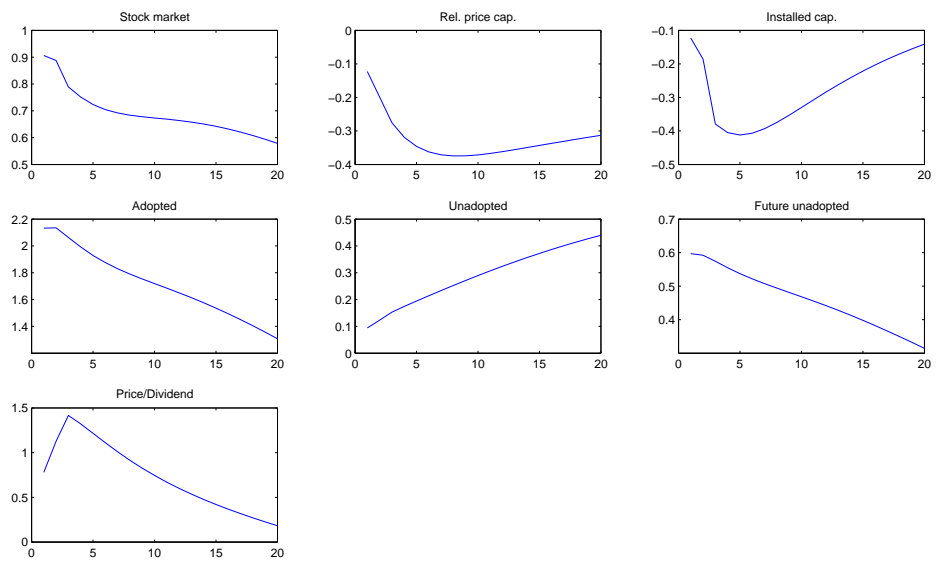


Figure 7: Estimated stock market and relative price of capital response to a TFP shock

Table 8: Stock market moments and Cambell-Shiller test

	Data		Model		V p-value H0: $\sigma(\text{data})=\sigma(\text{model})$	VI p-value H0: $\rho_1(\text{data})=\rho_1(\text{model})$
	I	II	III	IV		
	$\sigma$	$\rho_1$	$\sigma$	$\rho_1$		
$\Delta d$	0.11 (0.0036)	-0.09 (0.22)	0.034 (0.00034)	0.7 (0.16)	<.005	> 0.99
$\Delta q$	0.136 (0.0054)	-0.03 (0.26)	0.133 (0.0052)	0.63 (0.13)	> 0.995	> 0.995
q-d	0.38 (0.0425)	0.83 (0.12)	0.68 (0.1362)	0.99 (0.034)	> 0.995	> 0.995

Cambell-shiller (1988) test

$\sigma((q-d)')/\sigma(q-d)$	0.66	0.44
$\text{corr}((q-d)',q-d)$	0.87	0.53

Moments based on annual observations for period 1984-2006. Standard deviations in parenthesis. Variables are defined as follows: d is the (log) nominal dividend, q is the (log) nominal stock price,  $\sigma(x)$  denotes the standard deviation of x,  $\text{corr}(x,y)$  the correlation between x and y,  $\rho(1)$  denotes the first order autocorrelation,  $(x)'$  denotes the year ahead forecast of x based on a two variable VAR with one lag as in Cambell-shiller (1988) table 5, Model version 2. Cambell-Shiller (1988) test: First row contains ratio of standard deviation of forecasted price-dividened ratio over standard deviation of actual price dividend ratio. Second row contains the correlation between the two.

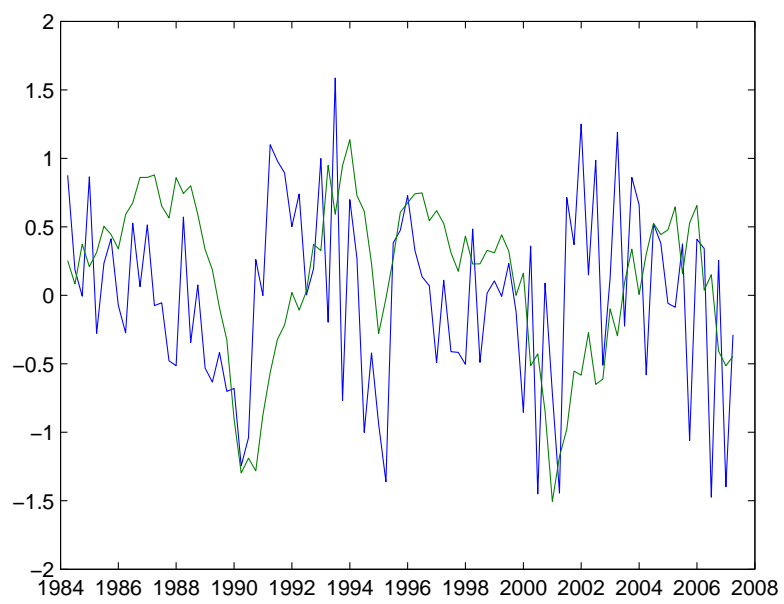


Figure 8: Historical Decomposition Output Growth: green data, blue counterfactual (Innovation Shock)

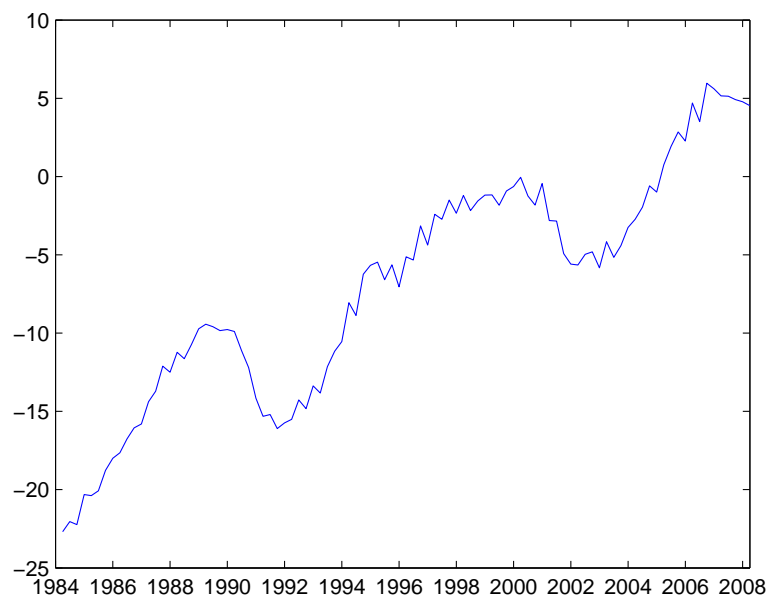


Figure 9: Growth Rate Innovation Shock

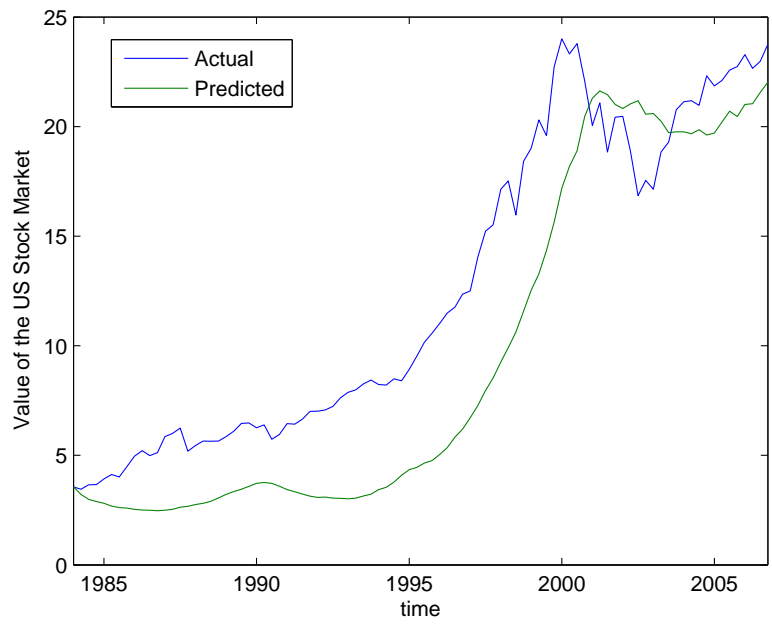


Figure 10: Stock market