News, technology adoption and economic fluctuations

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Abstract

Are shocks about future technology expansionary? We show that this is the case if agents control the speed at which new technologies are adopted in the economy (i.e. if adoption is endogenous). In response to news about future technologies, agents want to substitute consumption and leisure for investments in adoption and new capital and work. This substitution effect overcomes the wealth effect from the arrival of new technologies. If technology adoption is exogenous, this substitution effect disappears and the news about future technology are contractionary. Shocks on future technology cause counter-cyclical movements in the relative price of capital and large pro-cyclical fluctuations in the stock market, which lead output generating a mean-reverting price-dividend ratio. We estimate a model with four other shocks and find that shocks on future technologies are responsible for 45 percent of the fluctuations in output growth. A version of the model augmented with nominal rigidities further increases the importance of future technology shocks. When estimating this version of the model we also find that monetary policy shocks, propagated through the technology adoption mechanism, are an important source of output fluctuations.

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JEL Classification: E3, O3.

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 only major example. But even here there is controversey. Not all recessions are preceded by major oil price spikes and there is certainly little

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evidence that major expansions are fueled by oil price booms. Further, given its low cost share of production, there is debate over whether in fact oil shocks alone could be the source of major output swings.

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 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, due tend to lead the cycle (e.g., Stock and Watson, 200?). In addition, Beaudry and Portier refine this evidence by showing that stock prices uncorrelated with current total factor productivity help predict future productivity. That stock prices move to anticipate subsequent output fluctuations independently of current observable disturbance lends support to the news shock hypothesis.

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 correcting the 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, Ilciq(?), Motto and Rostagno (2008) 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 persistent overly in monetary policy.

In this paper we develop alternative expectations based theory of fluctuations that is based on the evolution of an economy's technology frontier. In particular we make the distinction between potential technologies versus those that have been adopted and are useable for production. As in Comin and Gertler (2006), further, we assume that adoption is costly and, on average, a time consuming process. We take the evolution of potential technologies as exogenous.[1] A shock to the process, 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 ultimately leads to a shift in labor demand that offsets the wealth effect. This endogenous and pro-

[1] It is strightforward, following Comin and Gertler (2006) to endogenize the arrival rate of new technologies. In this more comprehensive model, the shocks about future technologies would affect the productivity of the R&D technology.

cyclical movement of adoption, further, 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.

Our model also broadly captures the cyclical pattern of stock prices movements that is suggestive overall of the news shock approach. 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 technoligies. Revisions in beliefs about this added component of expected earnings allows us to capture both the highly 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 only come on line in the future, the model also has the property that the price-earnings ration is highly mean reverting, as is consistent with the evidence.

In section 2 we present a simple expository model of our news shock as a prelude to an estimated model that we present in section 5. The model adds to a simple real business model endogenous embodied technological change. We do so by introducing an expanding variety of capital goods that are used in the production of final capital goods. The rate of change of potential intermediate capital goods is endogenous. Adoption of these goods is endogenous, however, we describe below. We focuse on embodied as opposed to disembodied technological change because the recent empirical macroeconomics literature has stressed investment shocks as the main source of business cycle fluctuations.

In section 3 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. Because adoption of technologies is costly, news of potential future growth does not lead to a "perverse" response of hours. We also show that the shock produces a realistic cyclical response of stock prices. We also show that with exogenous adoption, the model cannot produce the correct cyclical pattern in the responses of output and hours, as well as the other key variables.

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 embodied technological change endogenous whereas in the standard model it is exogenous. Here our goal is 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 all the our parameters. Section 6 reports the estimates as well as the variance decomposition and a historical decomposition. Our main finding is that the implications of our news shock that we found from our simple calibrated model are robust to using a richer estimated model. Further, shocks to future technology are an important driver of business fluctuations. Concluding remarks are in section 7.

2 Baseline Model

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:

$$Y_t = C_t + I_t + G_t + H_t + O_t \tag{1}$$

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

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

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. The 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 of New Capital

We begin with the non-standard feature of the model: the creation of new capital. There are two stages to this process. First, a continuum of N_t^K differentiated firms construct new capital. Each uses as input a continuum of A_t differentiated intermediate capital goods purchased from suppliers. Let $J_t\,(r)$ be new capital produced by firm r and $I_t^r(s)$ the amount of intermediate capital the firm employs from supplier s. Then

$$I_t\,(r) = \left(\int_0^{A_t} I_t^r(s)^{\frac{1}{\theta}} ds \right)^{\theta} \tag{3}$$

with $\theta > 1$. Note that each supplier s of intermediate capital goods has a bit of market power. Profit maximization implies that she sets the price of the s 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.

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

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

$$J_t = \left(\int_0^{N_t^K} I_t\left(r\right)^{\frac{1}{\mu^K}} dr \right)^{\mu^K} \tag{4}$$

with $\mu^K > 1$.

We allow the number of capital producers N_t^K to be endogenously determinded 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 $\overline{P}_t^k$ 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 capital good producer, o_t^k is

$$o_t^k = b^k \overline{P}_t^k K_t$$

where b^k is a constant, $\overline{P}_t^k$ 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 (2005), we think of operating costs as increasing in the technological sophistication of the economy, as measured by $\overline{P}_t^k K_t$.At the margin, the profits of capital producers must cover this operating cost, which as we show later pins down N_t^k

2.3 Technology

The efficiency of the production of new capital goods depends on the number of "adopted" new intermediate goods A_t. We characterize next the process that governs the evolution of this variable.

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 protype must be successfully adopted. The adoption process, in turn, involves a costly investment that we describe below. We also allow for obsolesence of these products.

Let Z_t denote the total number of intermediate goods in the economy at time t, including both previously adopted goods and "not yet adopted" prototypes. The law of motion for Z_t is as follows:

$$Z_{t+1} = (\chi_t + \phi)Z_t$$

[2] 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 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. Note that the probability that an intermediate good becomes obsolete, $1 - \phi$ is independent of whether it has been adopted, capturing the idea that some new inventions simply do not pan out even before they reach the adoption stage. For simplicity we keep the obsolence probability the same across adopted and unadopted goods, though this assumption is not critical to our results.

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 capital 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. 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 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 units of final output. Its success probability λ_t is increasing in adoption expenditures, follows:

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

with $\lambda' > 0$, $\lambda'' < 0$, where h_t 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

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

We presume that past experience with adoption, measured by the total number of projects adopted A_t, 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.

[3]Comin (2007).

The value to the adopter of successfully bringing a new technology into use, v_t, is given by the present value of profits from operating the technology. Profits π_t 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, as

$$v_t = \pi_t + (1-\phi)E_t\left[\beta\Lambda_{t,t+1}v_{t+1}\right]. \tag{5}$$

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 be the value of acquiring an innovation that has not yet been adopted yet. j_t is given by

$$j_t = \max_{h_t} -h_t + E_t\{\beta\Lambda_{t,t+1}(1-\phi)[\lambda_t v_{t+1} + (1-\lambda_t)j_{t+1}]\} \tag{6}$$

Optimal investment in adopting a new technology is given by:

$$1 = E_t\left[\beta\Lambda_{t,t+1}(1-\phi)\Gamma_t\lambda'\left(\Gamma_t h_t\right)\left(v_{t+1} - j_{t+1}\right)\right] \tag{7}$$

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

2.4 Production

We now turn to the more conventional aspects of the model and begin with the production of output. As with capital goods production, there are two stages: final and intermediate. Technological change in this sector, however is completely exogenous.

There is a final output composite which as we noted earlier is one of five purposes: consumption, investment, government spending, adopting available technologies and paying firm operating costs. The composite Y_t is a CES aggregate of N_t differentiated final goods, where $Y_t(j)$ is the output of final good producer j:

$$Y_t = \left(\int_0^{N_t} Y_t(j)^{\frac{1}{\mu}}dj\right)^{\mu}, \text{ with } \mu > 1, \tag{8}$$

where μ is inversely related to the price elasticity of substitution across goods. To further maintain symmetry with capital goods producers, we allow the number of final goods firms N_t to be determined by a free entry condition that holds every instant. In particular, the per period operating cost of a final good producer is

$$o_t = b\overline{P}_t^k K_t$$

where as with capital goods producing firms we scale operating costs by the factor $\overline{P}_t^k K_t$ in order to maintain balanced growth.

Each final good firm produces a differentiated good using the following Cobb-Douglas technology:

$$Y_t(f) = X_t \left(U_t(f)K_t(f)\right)^{\alpha} \left(L_t(f)\right)^{1-\alpha} \tag{9}$$

where X_t is disembodied productivity and ς_t is an i.i.d innovation:[4]

$$X_t = (1+g)X_{t-1} \exp^{\varsigma_t}$$

In addition, U_t denotes the intensity of utilization of capital. Following Greenwood, Hercowitz and Huffman (1988), we 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.

2.5 Households

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:

$$E_t \sum_{i=0}^{\infty} \beta^i \left[\ln C_{t+i} - \mu^w \frac{(L_{t+i})^{1+\zeta}}{1+\zeta} \right] \tag{10}$$

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

$$C_t = W_t L_t + \Pi_t + [D_t + P_t^k]K_t - P_t^k K_{t+1} + R_t B_t - B_{t+1} - T_t \tag{11}$$

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 (10) subject to (11).

3 Symmetric equilibrium

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

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

Evolution of endogenous states, K_t and A_t:

$$K_{t+1} = (1 - \delta(U_t))K_t + (P_t^K)^{-1} I_t \tag{12}$$

$$A_{t+1} = \lambda_t [Z_t - A_t] + \phi A_t \tag{13}$$

Resource Constraint:

$$Y_t = C_t + G_t + \frac{P_t^k I_t}{\mu_k \theta} + \overbrace{\frac{\mu - 1}{\mu} Y_t + \frac{\mu_k - 1}{\mu_k} I_t}^{\text{Entry Costs}} + \overbrace{(Z_t - A_t) h_t}^{\text{Adoption Costs}} \tag{14}$$

Aggregate production

$$Y_t = X_t N_t^{\mu-1} \left(U_t K_t\right)^{\alpha} L_t^{1-\alpha} \tag{15}$$

Factor market equilibria for L_t and U_t:

$$(1 - \alpha)\frac{Y_t}{L_t} = \mu\mu^w L_t^{\zeta} / (1/C_t) \tag{16}$$

$$\alpha \frac{Y_t}{U_t} = \mu \delta'(U_t) P_t^K K_t \tag{17}$$

Consumption/Saving

$$E_t\{\beta \Lambda_{t+1} \cdot [\alpha \frac{Y_{t+1}}{\mu K_{t+1}} + (1 - \delta(U_{t+1}) P_{t+1}^K] / P_t^k\} = 1 \tag{18}$$

where $\Lambda_{t+1} = C_t / C_{t+1}$.
Optimal adoption of innovations

$$1 = (1 - \phi)\beta E_t \left[\Lambda_{t+1} \frac{A_t}{o_t^k} \lambda' \left(\frac{A_t}{o_t^k} h_t \right) (v_{t+1} - j_{t+1}) \right] \tag{19}$$

with

$$v_t = (1 - \frac{1}{\theta}) \frac{P_t^K I_t}{A_t} + (1 - \phi)\beta E_t \left[\Lambda_{t+1} \frac{A_{t+1} v_{t+1}}{A_t} \right]$$

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

where

$$\lambda_t = \lambda_0 \left(\frac{A_t h_t}{o_t^k} \right)^{\rho}$$

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

$$\begin{aligned} \frac{\mu - 1}{\mu} \frac{Y_t}{N_t} &= o_t \\ \frac{\mu_k - 1}{\mu_k} \frac{I_t}{N_t^K} &= o_t^k \end{aligned} \tag{20}$$

Relative price of retail and wholesale capital

$$\begin{aligned} P_t^K &= \mu_k \theta (N_t^k)^{-(\mu-1} A_t^{-(\theta-1)} \\ \overline{P}_t^K &= \theta A_t^{-(\theta-1)} \end{aligned} \tag{21}$$

figure

Observe that the wholesale price of capital varies inversely with the number of adopted technogies. 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 the embodied technological change is exogenous. News of a future decline in the relative price of capital leads to the expectation of greater capital accumulation in the future an hence higher higher output for a given labor supply. Current consumption increases, inducing a negative effect on labor supply, as equation (16) 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 news shocks.

4 Model Simulations of "News" Shocks

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

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 0.99, to match the steady state share of non-residential investment to output. Based on steady state evidence we also choose the following number: (the capital share) $\alpha = 0.33$; (government consumption to output) $G/Y = 0.2$; (the depreciation rate) $\delta = 0.02$; and (the steady state utilization rate) $U = 0.8$.[5] 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 1.2.

We next turn to the "non-standard" parameters. Following Comin and Gertler (2006), we set the gross markup charged by intermediate capital goods to 1.66. 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 the mean of χ_t and the obsolescence rate. To match the average annual growth rate of the Gordon quality adjusted price of capital relative to the BEA price of consumption goods and services (-0.026), we set the average of χ_t to 1.975 percent. The growth rate of GDP in steady state depends on the growth rate of new intermediate capital goods and on the exogenous growth rate of X_t. To match the average annual growth rate of non-farm business output per working age person over the postwar period (0.024) we set the growth rate of X_t to 0.27 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 two parameters to parameterize the function $\lambda(.)$ as follows:

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

[5] 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 $\bar{\lambda}$ 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 $1/\lambda + 1$. 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.[6] For these reasons, we set $\bar{\lambda}$ to match an average adoption lag of 4 years.[7]

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 and for a version of our model where technologies diffuse at a fixed speed. In particular, the solid line represents the response of our model while the dashed line represents the response of the model with exogenous diffusion.

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

[6] Comin and Hobijn (2007) and Comin, Hobijn and Rovito (2008).

[7] 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.

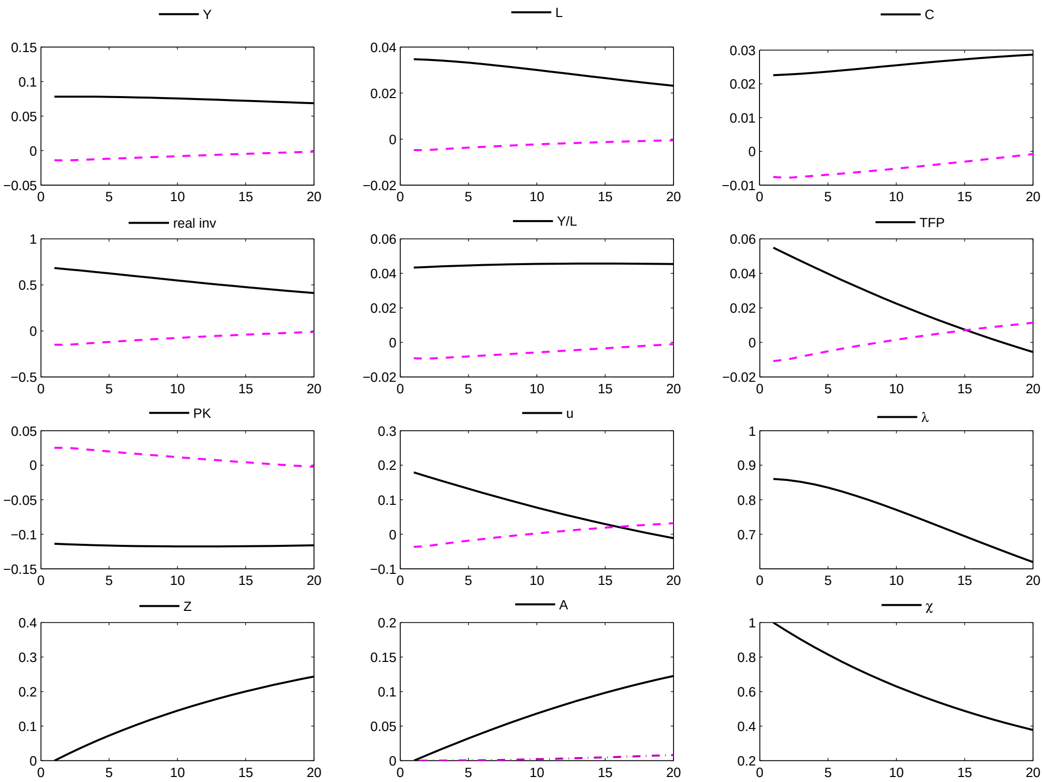

Figure 1: Simulated model: endogenous vs exogenous adoption

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 illustratd 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 variaty 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 reponsible 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, capacity utilization, net entry and also in consumption. Eventually, the new technologies are adopted leading to a boom. This however happens 20 quarters after the news about future technology arrives.

5 The stock market

As Beaudry and Portier (200?) emphasize, any news-driven theory of business fluctuations muct 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 problems is that in models in embodied technological as well as in the data, changes 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, with some form of intangible capital present, it is possible to generate large movements in asset prices. In our model this intangible capital takes the form of with the rights to make a profit out of current and future adopted intermediate goods. And, 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.

$$\begin{aligned} Q_t &= \varphi_1 \left[\overbrace{P_t^k K_t}^{\text{Replacement value of capital}} + \overbrace{A_t(v_t - \pi_t)}^{\text{Value of adopted technologies}} \right] \\ &+ \varphi_2 \left[\overbrace{(w_t + x_t)(Z_t - A_t)}^{\text{Value of existing not adopted technologies}} + \overbrace{E_t \sum_{\tau=t+1}^{\infty} \Lambda_\tau w_\tau (Z_\tau - \phi Z_{\tau-1})}^{\text{Value of future non-adopted technologies}} \right] \end{aligned} \tag{22}$$

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 (22). The second term reflects the market value of adopted intermediate capital goods and therefore currently used to produce new capital. 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. So we try to construct a measure of the market value implied by the model for these companies. This is the rationale for introducing the parameters φ_1 and φ_2 which roughly speaking represent the share of publicly traded companies in the total value of corporations.

The two terms multiplied by φ_1 represent the value of installed capital and the value of adopted intermediate goods of companies that currently operate. By multiplying both of them by the same parameter, φ_1, we are assuming that publicly traded companies roughly have the same share of capital and adopted intermediate goods. Even under this assumption, calibrating φ_1 is not trivial since we do not have very good estimates of the capital stock disaggregated between publicly traded and non-publicly traded companies. Hall (2003) estimates that in 1999, the capital stock of publicly traded companies was worth 4 trillion dollars. This represented approximately 20 percent of fixed private capital. Based on this, we set φ_1 to 0.2.

In 1999, the market value of traded companies plus their corporate debt was approximately 22.4 trillions (i.e. 2.3 times GDP). Given the value of φ_1, and the steady state value implied by our model for the four components, this yields an estimate of φ_2 of 0.02. That is, existing stock market measures capture only 2 percent of the value of current and future not adopted technologies.

Figure 2 displays the response of the relative price of capital and the stock market as measured by (22) 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 teh relative price of capital reduces the replacement cost of physical capital leading to a drop in the first term in (22). 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 martet 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 had some key features that have proven to be helpful in permitting the conventional macroe-

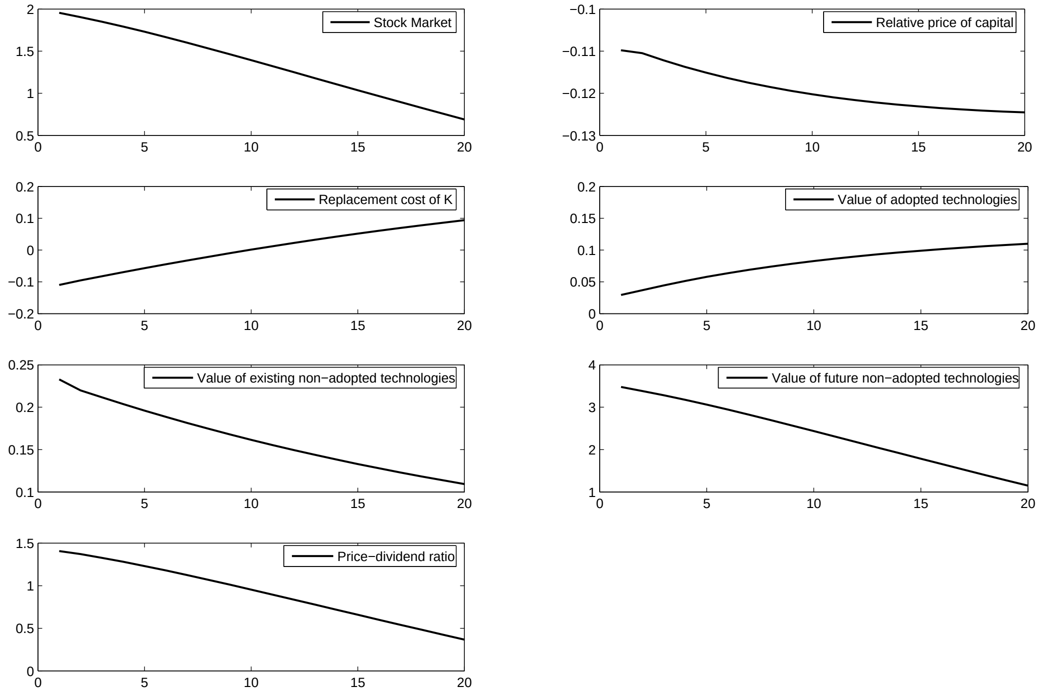

Figure 2: Simulated model: The stock market

conomic 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 news shocks 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:

$$E_t \sum_{i=0}^{\infty} \beta^i b_{t+i} \left[\ln(C_{t+i} - \upsilon C_{t+i-1}) - \mu_{t+i}^w \frac{(L_{t+i})^{1+\zeta}}{1+\zeta} \right] \tag{23}$$

where the parameter υ, 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 obtrain identification.

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

$$K_{t+1} = (1-\delta_t)K_t + (P_t^k)^{-1} I_t \left(1 - \gamma \left(\frac{I_t}{(1+gy-gq)I_{t-1}} - 1\right)^2\right) \tag{24}$$

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 Schaumberg (2008)), the relative price of capital is an exogenous disturbance. In our model it is endogenous. As equation (21) suggests, P_t^k depends inversely on the volume of adopted technologies A_t 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 monopolitically competitive intermediate goods producing firms (see equation (8)) 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 Schaumberg (2008), we used a formulation of staggered price setting due to (1983), modfied 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:

$$P_{t+1}(j) = P_t(j)\left(\Pi_t\right)^{\iota_p}\left(\Pi\right)^{1-\iota_p} \tag{25}$$

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.

$$E_t\sum_{s=0}^{\infty}\xi^s\beta^s\Lambda_{t,s}\{[\frac{P_t^*}{P_{t+s}}\left(\prod_{j=0}^{s}\left(\Pi_{t+j}\right)^{\iota_p}\left(\Pi\right)^{1-\iota_p}\right)]Y_{t+s}(j)-W_{t+s}N_{t+s}(j)-D_{t+s}K_{t+s}(j)\} \tag{26}$$

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

$$Y_t(j) = (\frac{P_t(j)}{P_t})^{\frac{-\mu}{\mu-1}}Y_t \tag{27}$$

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

$$P_t = [(1-\xi)(P_t^*)^{\frac{\mu-1}{\mu}} + \xi(P_{t-1})^{\frac{\mu-1}{\mu}}]^{\frac{\mu}{\mu-1}} \tag{28}$$

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:

$$\frac{R_t^n}{R^n} = \left(\frac{R_{t-1}^n}{R^n}\right)^{\rho_r}\left(\left(\frac{\Pi_t}{\Pi}\right)^{\phi_p}\left(\frac{Y_t}{Y_t^0}\right)^{\phi_y}\right)^{1-\rho_r}\exp(\mu_{mp,t}) \tag{29}$$

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 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 inflaton 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 new shocks that Christiano, ?, Motto and Rostagno (2007) emphasize. One widely employed fricion that we do not add in 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 treatment of the investment disturbance. The standard treats this disturbance as an exogenous shock to the relative price of capital. 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 1954:I to 2004:IV on six key macroeconomic variables in the US economy: output, consumption and investment, inflation, nominal interest rates and hours. The vector of observable variables is:

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

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 diving the nominal series (GDP) by population and the GDP Deflator . Real series for consumption and investment are obtained similarily, but consumption corresponds only to personal consumption expenditures of non-durables and services, while investment is the sum of personal consumption expenditures of durables and gross private domestic 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 six 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 standard models typically also include a shock to the relative price of capital. Here the evolution of the relative price is endogenous. The key underlying exogenous disturbance further is growth rate of potential new intermediate capital goods. We include this shock as the sixth in the model. Since it provides a signal of the likely future path of P_t^k, we interpret it as our "news shock."

We continue to calibrate the parameters of the emodied 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 1 presents the prior distributions for the structural parameters along with the posterior estimates. Tables 2 presents the same information for the estimates of the serial correlaton and standard deviation of the stochastic processes. To maintain comparability with the literature, for the most part we we employ the same priors as in Justiniano, Primiceri and Schaumberg (2007).

Table1: Prior and Posterior Estimates of Structural Coefficients

Coefficient	Prior Distribution	Posterior mean	5%	95%
υ	Beta (0.50,0.10)	0.525	0.508	0.545
ρ_r	Beta (0.70,0.10)	0.664	0.654	0.671
ξ	Beta (0.6,0.05)	0.864	0.865	0.866
ι_p	Beta (0.35,0.05)	0.246	0.244	0.249
ψ	Normal (1.00,0.50)	1.58	1.570	1.581
ϕ_p	Normal (1.70,0.30)	1.560	1.547	1.572
ϕ_y	Gamma(0.125,0.10)	0.351	0.350	0.352
ζ	Gamma (2.00,0.75)	1.862	1.836	1.900
$\frac{\delta'' U}{\delta'}$	Gamma (0.10,0.15)	0.186	0.185	0.0.186

Table 2: Prior and Posterior Estimates of Shock Processes

Coefficient	Prior Distribution	Posterior mean	5%	95%
ρ_b	Beta (0.6 0.15)	0.578	0.571	0.585
ρ_m	Beta (0.6,0.15)	0.603	0.603	0.604
ρ_w	Beta (0.6,0.15)	0.820	0.810	0.830
ρ_{rd}	Beta (0.8,0.15)	0.987	0.986	0.987
ρ_g	Beta (0.6,0.15)	0.894	0.893	0.894
σ_{rd}	IGamma (0.5, ∞)	0.644	0.635	0.654
σ_w	IGamma (0.5, ∞)	0.614	0.608	0.622
σ_g	IGamma (0.5, ∞)	0.585	0.582	0.589
σ_b	IGamma (0.50, ∞)	0.732	0.730	0.734
σ_m	IGamma (0.1, ∞)	0.071	0.065	0.077
σ_x	IGamma (0.5, ∞)	0.511	0.504	0.518

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 3 present the standard deviations of several select variables. For comparision, we also present the same results for the model with exogenous adoption and also a benchmark model with an exogenous price of capital.

Table 3: Standard Deviatons

Variable	Data	End. Adopt.	Exog. Adopt.	Benchmark
Output growth	0.94	[1.16 1.22 1.28]	[1.91 1.99 2.1]	[2 2.23 2.45]
Consumption Growth	0.51	[0.49 0.55 0.64]	[0.19 0.20 0.22]	[0.32 0.42 0.49]
Investment Growth	3.59	[3.35 3.41 3.45]	[1.6 1.7 2]	[15.3 18.2 20.6]
Hours	2.8	[1.79 1.85 1.91]	[2.2 2.6 2.9]	[1.65 3.16 4.2]

Overall, our baseline model with endogenous adoption is most in line with data. Each of the models produces too much output growth volatility (a well know issue confronting this class of DSGE models), though ours is least out of line. Our model does a particularly good job of capturing investment growth and hours volatility. Though we do not report the results here, the marginal likelihood of our baseline model is significantly higher than that of the other two.

To assess how important our shock is as a business cycle driving force, Table 3 reports the contribution of each shock to the unconditional variance of four observable variables: output, consumption and investment growth and level of hours. We refer to the disturbance to the growth rate of potential new intermediate capital goods (our "news" shock) as the "innovation" shock.

Table 4: Variance Decomposition

Observable	Labor Supply	Inter. Preference	Innovation	Neutral Tech.	Gov. Cons.	Monetary
ΔY_t	1.74	23.23	47.78	22.66	0.73	3.86
ΔI_t	18.22	0.16	73.86	7.18	0.28	0.30
ΔC_t	1.57	5.82	48.85	9.92	24.05	9.79
L_t	24.77	0.43	59.43	14.09	0.89	0.38

The first row of the table shows that the innovation shock is the main driving force. It accounts for 48% of the variation in output growth, 74% of the fluctuations in investment growth, 49% of consumption growth and 59% of hours.
This result is not entirely surprising since Justiano, Primiceri and Tambalotti (2008) similarly find that a shock to the relative price of capital is the main

driving force. Our model, though, provides a theory of the fluctuations of the relative price of capital at the high and medium term frequencies and relates them to a more primitive driving force that can be more easily related to the US experience during the second half 1990s: the shock to the growth rate of new potential capital goods.

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 and consumption. The response of output and investment in the estimated model, however, is strongly-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. Here two factors are relevant. The introduction of the various frictions has likely dampened the overall hours response. The conventional models, however, are able to obtain a more significant response of hours to investment shocks by incorporating wage rigidity. In the next draft of this paper we will explore this option.

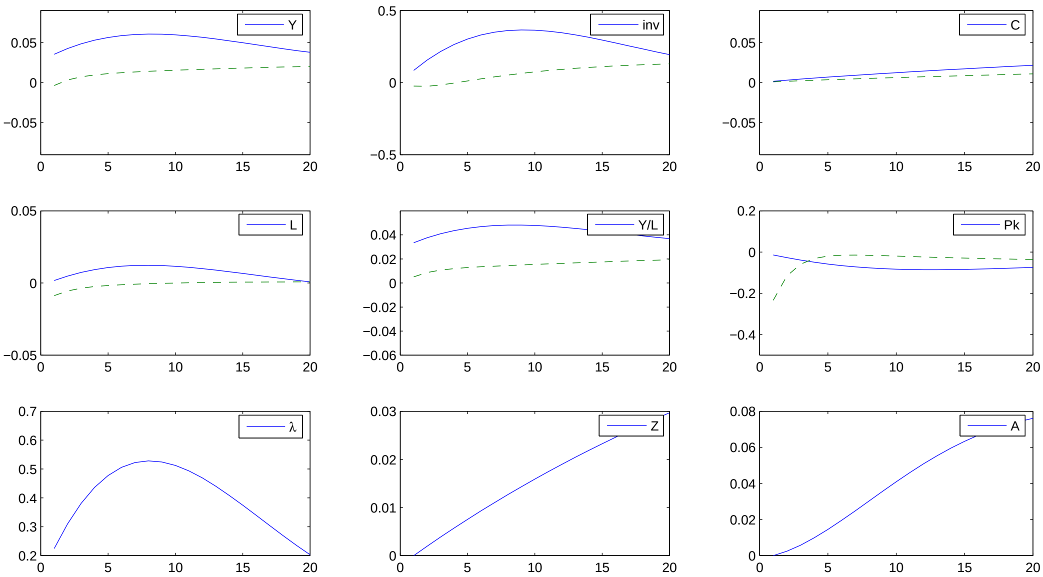

Figure 3: Estimated model sticky prices: Endogenous (solid) vs exogenous adoption (dashed)

One possibility is that the monetary policy rule may be playing a role in propagating our news shock by being overly accomodating. We explore this

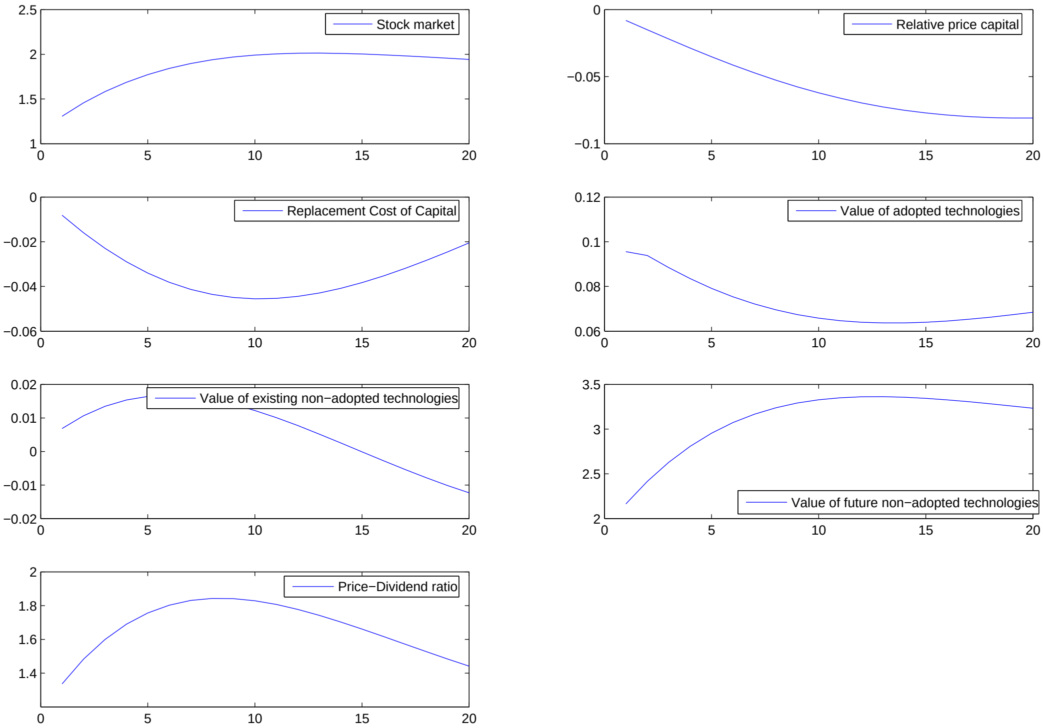

Figure 4: Estimated model: The stock market

possibility by shutting off the price rigidity in the model and instead allowing prices to be perfectly flexible. In the process, we keep the estimated structural parameters from the full blown model. Figure 4 reports the results. Note that the results for the sticky and flexibile 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 a news shock.

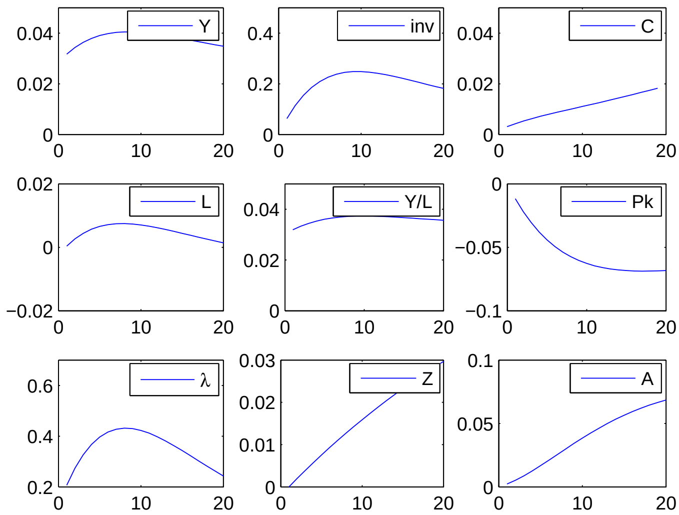

Figure 5: Estimated model flexible prices: Endogenous adoption

Finally, it is interesting examine a historical decompostion of the data. Figures 6 plots the implied growth rate of new intermediate capital goods (our news shock). 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 drop sharply around 2002, a period where investor expectations clearly turned pessimistic. Figure 7 plots the series for investment growth induced by our news shocks together with the actual investment growth series. Not surprisingly, the contribution of the shock to cyclical investment growth is substantial. It clearly plays a role in both the boom-bust episodes pre-1980 as well as in the relative rapid increase in investment in the mid 1990s and the collapse of early 2000. 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, though somewhat surprisingly in light of the investment results, 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. In the next version of the model we plan to explore adding wage rigidity.

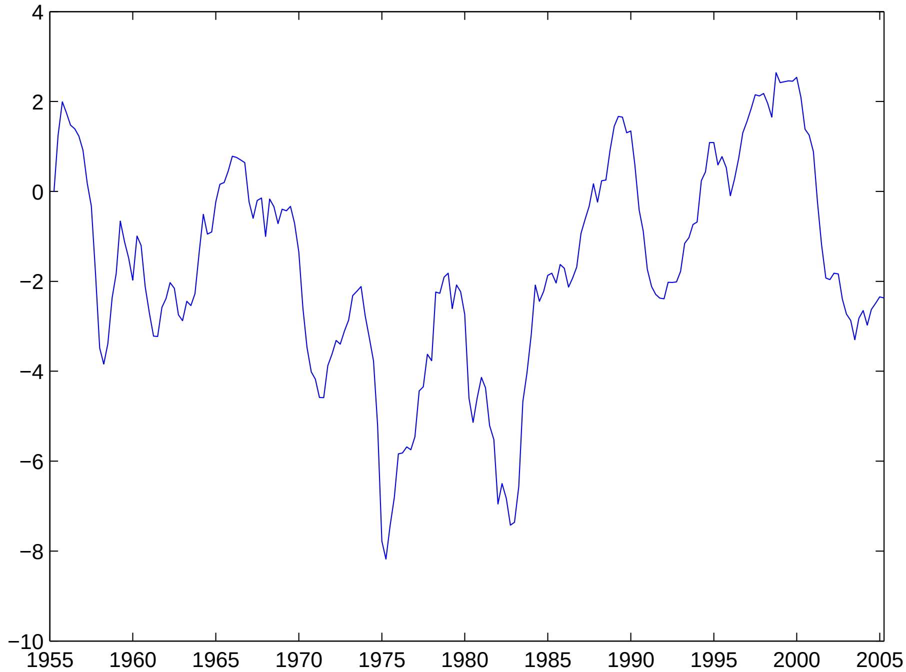

Figure 6: Innovation Shock

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. First, once endogenous technology adoption is incorporated to an otherwise standard model, news about future technology generate booms in output employment and investment. Second, by 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. Third, our model accounts for the volatility of the stock market, its lead over output and the mean reversion of the price-dividend ratio. Fourth, the model with endogenous adoption provides a superior fit to the data (relative to the alternative

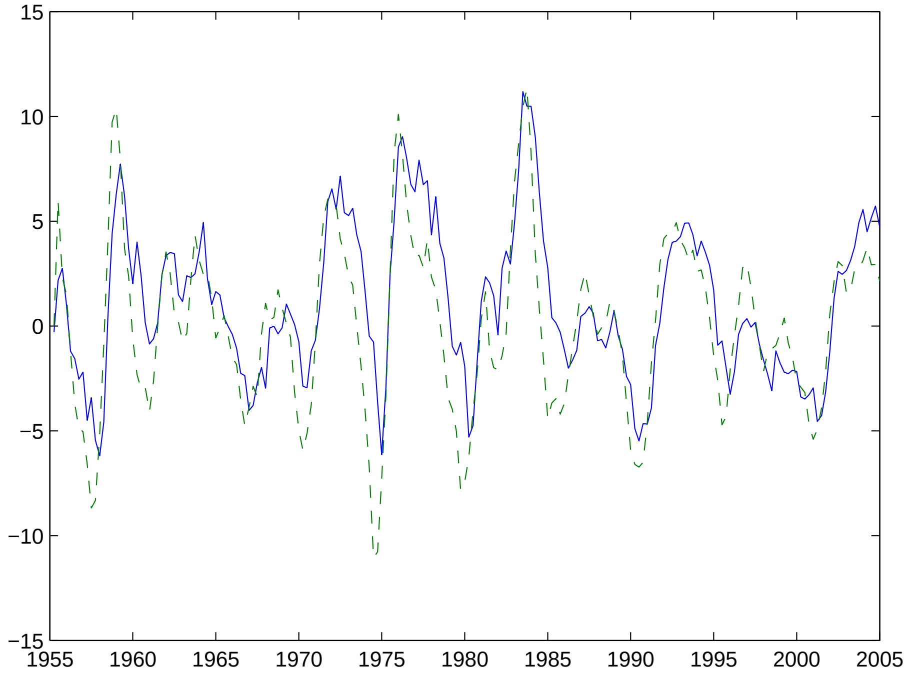

Figure 7: Historical Decomposition of Investment Growth; data in solid, counterfactual in dashed

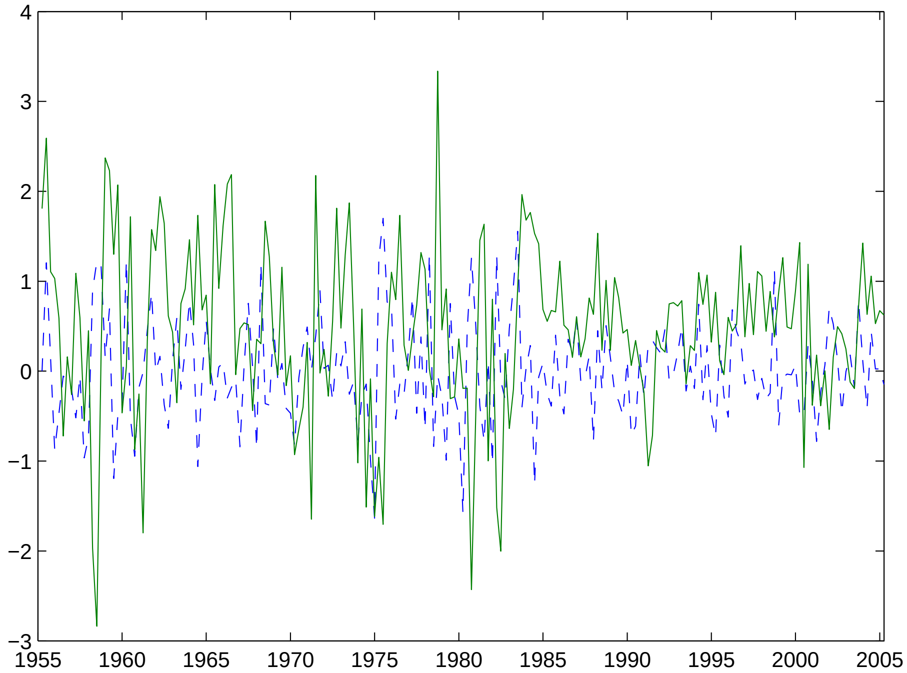

Figure 8: Historical Decomposition of Output Growth; data in solid, counterfactual in dashed

without) based on its log-likelyhood function as well as the volatility of the main macro variables. Fifth, the shock about future technologies is the main shock in accounting for business fluctuations. In particular, it explains about fifty percent of output growth, employment growth and consumption growth fluctuations and about 70 percent of investment growth fluctuations. Sixth, the historical evolution of the shock about future technologies is consistent with run up during the second half of the 1990s in productivity and investment.