Endogenous Technological Change and The Great Recession

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Abstract

This paper studies the importance of the firms' technology upgrading decisions for the persistence of business cycles. We develop and estimate a standard business cycle model modified to allow firms to upgrade technology in response to business cycle conditions. Technology upgrading decisions introduce new state variables that propagate shocks affecting the duration of business cycles. Our model generates a decline in TFP by 4.3% and in embodied productivity by 5.4% from 2007:IV to 2012:IV. Without the endogenous upgrading mechanisms, in 2012:IV, output would be 4% below trend instead than the actual 8.6% that we observed.

Keywords: Business Cycles, Endogenous Technology Adoption, R&D, Credit Shocks, Great Recession.

JEL Classification: E3, O3.

1 Motivation

Macroeconomists have long been puzzled by the persistence of business cycle fluctuations. Stardard macroeconomic models are unable to generate significant propagation of business cycle shocks (Cogley and Nason, 1995). Therefore, they struggle to explain why some recessions are very protracted. The Great Recession has been one of the deepest and longest recessions the U.S. economy has experienced over the post-war period. The NBER dating committee determined that the through of the Great Recession was reached in September 2009. However, the post-recession recovery has been very slow preventing output from coming back to trend (Figure 1).

There is wide consensus that the recession originated in a credit disruption which started around the fourth quarter of 2007. However, there is ample evidence that financial markets recovered relatively quickly. Figure 1 plots the evolution of the spread between the yields on corporate bonds and 10-year government bonds (GZ, 2012) which is a proxy for the credit conditions faced by companies. It shows a dramatic deterioration of credit conditions starting at the end of 2007 and that reach a zenith by the end of 2008 when the spread peaked at 7.65%. However, the disruption to credit markets was transitory and by the beginning of 2010, the GZ spread had almost fallen to pre-recession levels. Hence, the puzzle of how a transitory credit disruption may have such a protracted effect on economic activity.

On November 20th 2012, Ben Bernanke reflected about the persistence of the great recession in a speech at the New York Economic Club. "As background for our monetary policy decision-making, we at the Federal Reserve have spent a good deal of effort attempting to understand the reasons why the economic recovery has not been stronger. [...] one possibility is that financial crises, or the deep recessions that typically accompany them, may reduce an economy's potential growth rate, at least for a time."

As for the mechanisms, Bernanke hypothesized that "The pace of productivity gains–another key determinant of growth in potential output–may also have been restrained by the crisis, as business investment declined sharply during the recession; and increases in risk aversion and uncertainty, together with tight credit conditions, may have impeded the commercial application of new technologies and slowed the pace of business formation."

This paper studies the importance of the firms' technology upgrading decisions for the persistence of business cycles. To this end, we develop and estimate a standard business cycle model modified to allow firms to upgrade technology in response to business cycle conditions. Our model has two sectors that produce output and capital. In each sector, we allow for the endogenous development and diffusion of new technologies. These technology upgrading decisions affect the evolution of the stock of technologies available for production which become state variables that affect the dynamics of the economy. In response to recessionary shocks, firms cut their investments in developing and adopting new technologies slowing the rate at which new technologies are incorporated to production. As a result, productivity slowly deteriorates (relative to trend) amplifying and propagating the initial recessionary shock.

Before evaluating the significance of these effects by bringing the model to the data, we study the evolution of R&D expenditures and productivity measures. We document and summarize evidence that R&D and adoption expenditures are pro-cyclical and lead the evolution of productivity measures. In the specific case of the Great Recession, we document a drastic decline in R&D expenditures and a progressive and very significant decline in measures of both embodied and disembodied productivity in the U.S.

We bring formally the model to the data by using Bayesian methods to estimate key structural parameters and the stochastic processes that have shocked the U.S. economy since 1984. For comparison purposes, we also estimate a version of the model where technology is fixed at the balance growth path levels. Overall, the endogenous technology does a better job in fitting the data. It matches the volatility of output, consumption and investment at business cycle frequencies but generates fluctations in hours worked that are more volatile than in the data.

A variance decomposition reveals that credit shocks play a significant role in output fluctuations accounting the 21% of the variance of output growth and for 51% of the variance of H-P filtered output. Credit shocks have a larger effect in output fluctuations once we endogenize technology. This is the case because investments in upgrading technology amplify and propagate business fluctuations and credit shocks have a particularly strong effect on technology upgrading investments. Like other shocks, credit shocks affect the flow of profit faced developers and adopters of new

technologies because they affect aggregate demand. However, unlike other shocks, credit shocks also affect the rate at which companies discount the flow of future profits. As a result of this additional effect, credit disruptions cause more protracted fluctuations in technology which help explain historical variation in duration of business cycle fluctuations. The impact that credit shocks have on lower frequency technology dynamics explains why we find credit disruptions contribute more to fluctuations in HP-filtered levels than in growth rates.

Our model's account of the Great Recession is quite different from models with exogenous technology. The amplification of shocks by the invetsments in technology upgrading leads to a larger initial impact on output and hours worked of the deterioration of credit conditions during 2008. As a result, credit shocks account for virtually all the decline in output and hours in our model, while in the model with exogenous technology accounts for approximately half of the decline. When credit spreads come back to pre-crisis levels, the exogenous technology model predicts a relatively quick recovery. In contrast, in our model the slow rate of adoption of new technologies and the slowdown in their development is sufficient to seriously undermine the productive possibilities of the economy. Specifically, our model predicts a decline in disembodied productivity by 4.3% from 2007:IV to 2012:IV which is in line with what we have observed (Fernald, 2012). Similarly, our model predicts a deterioration of embodied productivity by 5.4% over the same period which is 55% of the decline we observe in the data.

To study the effect of low frequency movements in productivity, we conduct counterfactuals where we feed in the endogenous technology shocks to a model where technology evolves exogenously as in the balanced growth path. We find that the endogenous decline in productivity prevented macro aggregates (including hours worked) from recovering causing a very protracted recession. In our model output still was 8.6% below trend by 2012:IV. In contrast, in the exogenous technology counterfactual, output is only 4% below trend by the same date.

Related literature:

Comin and Gertler (2006), Comin (2009), Queralto (), Fatas (), Garcia- (2013).

The rest of the paper is organized as follows. Section 2 presents motivating evidence on the significance of the endogenous technology mechanisms in the propagation of business cycles. Section 3 introduces our model. Section 4 estimates it and evaluates

the importance of endogenous technology for business cycle fluctuations. Section 5 concludes.

2 Evidence on endogenous technology

Broadly speaking, there are two types of processes that affect the technologies used in production. The invention/development of new technologies, and their diffusion among producers. Next, we describe the existing evidence on the pro-cyclicality of these endogenous technology mechanisms, and investigate their evolution during the great recession.

R&D .– Previous studies have shown that R&D expenditures are highly correlated with the business cycle. The evidence dates back at least to Griliches (1990). Griliches, Fatas (2000) and Barlevy (2007) among others, show that the growth in real R&D expenditures is positively correlated with GDP growth. Comin and Gertler (2006) explore the cyclicality of R&D expenditures at lower frequencies. In particular, using a Band-Pass filter (e.g., Baxter and King, 1999) they isolate fluctuations with period between 2 quarters and 50 years in output and real corporate R&D. These cycles, which they define as medium term business cycles, include fluctuations at lower frequencies in addition to standard business cycle fluctuations. Comin and Gertler find that, over the period 1948-2001, R&D is even more pro-cyclical over the medium term busines cycle than over the conventionally defined business cycle.

Since we are interested in exploring the persistence of the effects of economic fluctuations on economic activity, we preserve low frequency fluctuations in the data we analyze. We achieve that by just linearly detrending all variables.[1] Because of structural changes in monetary policy around 1983/4, our analysis starts in 1983 and ends in 2011.[2] Figure 1a presents the evolution of two measures of real corporate R&D expenditures. R&D NSF measures R&D performed and financed by U.S. companies as measured by the NSF survey. R&D COMPUSTAT measures real R&D expenditures of publicly traded companies as reported in COMPUSTAT. In particular, we build this series by computing the average growth rate of R&D for companies that perform

[1] All our evidence extends to other filtering such as the Band-Pass approach followed by Comin and Gertler (2006).

[2] In the estimation, we use data from 1984QI to 2011QIV.

any R&D in any two consecutive years, constructing an R&D index by cummulating annual growth rates and linearly detrending the R&D index. The correlation between these series is 0.71.[3]

It is clear that real R&D expenditures are highly pro-cyclical. The correlation of GDP with R&D expenditures is 0.73 for the COMPUSTAT series and 0.65 for the NSF series (See Table 1). Beyond these statistics, it is clear from Figure 1a that detrended R&D expenditures were initialy low as the economy was still recovering from the 1982 recession, then thay raised over the 1980s expansion, and dropped during the 1991 recession (though the NSF measures falls with a lag). R&D increased very significantly during the 1990s expansion, and dropped significantly during the 2001 recession. Starting around 2003, detrended R&D stabilized and grew mildly until 2007. During the great recession both measures of R&D expednitures show very significant declines relative to trend.of approximately 15%. Between 2009 and 2011, R&D expenditures in publicly-traded companies do not seem to have recovered very significantly.

To explore the drivers of the drop in R&D investments during the great recession, we follow Barlevy (2007) and combine firm-level R&D data from COMPUSTAT with sectoral growth data from the BEA. In particular we construct 3-digit sector real value added and gross-output growth measures. Table 2A reports the estimates of the effect of sectorial demand growth on firm-level R&D growth during the period 2007-2011. All regressions contain a firm-level fixed effect to capture other firm-specific factors that may be affecting the dynamics of R&D (e.g., age, corporate culture, propensity to innovate,...). In addition to the specific measure of sectoral growth, the specifications differ in whether year fixed-effects are included and on whether we weight differently companies based on the share of R&D expenditures in 2007.

The main finding from Table 2A is that there is a positive association between both measures of growth in sectoral demand and growth in R&D expenditures at the firm-level.[4] To evaluate the robustness of this relationship, we control for an extensive

[3] Barlevy (2007) shows that the growth rate of these measures of corporate R&D expenditures is also high.

[4] Barlevy further shows that sectors where R&D is more cyclical have stock market values that are also more cyclical suggesting that R&D expenditures respond to the present discounted value of profits.

list of firm-level balance-sheet variables (See Table 2B).[5] This exercise yields two conclusions. First, the partial correlation we have observed during the great recession between sectoral growth and firm-level R&D growth is unaffected to controlling for the firms's balance sheet information. Second, firm cash-flows, both current and lagged, have been important drivers of R&D investments. In particular, we find that firms with higher current cash flows (before R&D expenditures) and lagged real cash flows (after R&D expenditures) have experienced higher growth in R&D. These findings suggest that both the decline in aggregate demand and the tightening of credit conditions have significantly led firm's to reduce their investments in upgrading production technologies in the economy (through R&D) during the great recession.

Diffusion .– A second channel by which technology upgrading affects productivity dynamics is the diffusion of new technologies. A pro-cyclical pattern of firms' investments in adopting new technologies should lead to a pro-cyclical speed of technology diffusion.[6] A pro-cyclical speed of diffusion of new (more productive) technologies should lead to pro-cyclical fluctuations in aggregate productivity.

The difficulty to measure the speed of technology diffusion or the magnitude of adoption investments has been a significant hurdle towards establishing the cyclicality of technology diffusion. Solow (1962) and the literature on embodied productivity that followed after, argue that many innovations are embodied in new capital equipment (and software). To the extent that investment consists in adding new, more productive forms of capital to the production process, investment should provide a reasonable proxy for the rate of diffusion of new technologies. (At least for those that are embodied in new capital.) Under these premises, the pro-cyclicality of real investment in equipment and software is evidence of the pro-cyclicality of the speed of diffusion of technologies embodied in new equipment. Figure 1A plots (linearly detrended) real investment in equipment and software between 1983 and 2011. The correlation of this series with GDP growth is 0.87 (See Table 1).

Comin (2009) looks more directly into the correlation between business cycle fluc-

[5] These include current year cash flow (before R&D expenses) and the residual cash flow in the previous year after R&D expenses, as well as current and lagged values of firm assets, firm liabilities, plant, property, and equipment, short-term debt (debt due within one year), and long-term debt. All variable are deflated with the GDP deflator and we include not only teh variables but also a second- and third-order term of all these variables in teh specifications reported in Table 1B.

[6] The idea that demand drives the adoption of innovations dates back to Schmookler (1962).

tuations and the diffusion of specific technologies. Using data on the fraction of potential adopters that have adopted each of 22 specific manufacturing technologies in the UK,[7] Comin fits a generalized logistic model that the speed of technology diffusion to vary over the cycle. The main finding from this study is that the speed of technology diffusion co-moves significantly with aggregate output fluctuations. In particular, the estimate of elasticity of the speed of technology diffusion with respect to medium term business cycle fluctuation in real GDP is 5.

Productivity .– To explore the significance of technology upgrading processes for fluctuations in aggregate productivity, we study the evolution of three measures of productivity. We study two measures of disembodied productivity: the TFP seris for the business sector from the BLS and the capacity corrected TFP series for teh business sector from Fernald (2012). In addition, we also focus on embodied productivity measured by the ratio of the GDP deflator over the equipment and software deflator (Greenwood et al., 1997).[8]

Figure 1B plots the evolution of these variables since 1984.[9] As with R&D and equipment and software investment, we linearly detrend the productivity measures. The Figure illustrates that the three measures of productivity have experienced large swings over the last 28 years. During the 1980s productivity gradually fell below the linear trend during the so-called productivity slowdown. In the mid 90s productivity accelerated as new information technologies were developed and incorporated to production. Starting around 2007, both TFP and embodied productivity started to deteriorate gradually but very significantly, leading to declines relative to trend between 2007 and 2012 of 2.6% for TFP, 5% for capacity-corrected TFP and 8.4% for embodied productivity.

[7] These include special presses, foils, wet suction boxes, gibberellic acid, automatic size boxes, accelerated drying hoods, electrical hygrometers, basic oxygen process, vacuum degassing, vacuum melting, continuous casting, tunnel kilns, process control by computer, tufted carpets, computer typesetting, photo-electrically controlled cutting, shuttleless looms, numerical control printing presses, numerical control turning machines and numerical control turbines. Data comes from Davies (1979).

[8] The series for both price deflators come from the BEA.

[9] At the high frequency both of these measures are pro-cyclical. The correlation between output growth and growth in these two measures of productivity between 1984 and 2011 is 0.57 in both cases.

By observing Figures 1a and 1b, one can appreciate a lead-lag relationship between productivity and measures of investment in technology upgrading. This is most obvious at the peaks and throughs of the series. While R&D and equipment bottom down in the early 90s and during the great recession and to peak in 2000, productivity measures seem to lag these investments in upgrading by three or four years. This observation is confirmed by Table 1B which computes the cross-correlogram between the measures of technology upgrading investments and productivity. R&D expenditures and equipment and software investments are not significantly correlated with TFP measures contemporaneously. As we lag R&D and equipment investment, the correlation with TFP measures increases. With a lag of three years, the correlations between technology upgrading investments and both TFP measures become significant. We find the highest correlations when R&D and equipment investment have a four year lead over TFP. The correlations then are 0.7 for R&D and 0.73 for equipment and software investment. We find a similar pattern between technology upgrading investments and embodied productivity or in capacity-corrected TFP. The key difference is that for embodied productivity, the contemporanous correlations are higher than for both TFP measures .

Taken together, we find these observations compelling evidence that firms' technology upgrading investments vary pro-cyclically and that lead to significant fluctuations in aggregate productivity with a three to four year lag. Next we develop a model that helps us evaluate more formaly the role of endogenous technology upgrading on low frequency fluctuations in productivity and output, and the importance of these forces during and after the great recession.

3 Model

The framework we develop is based on a standard monetary business cycle model with Calvo price-setting rigidities, habit formation and adjustment costs to the flow of investment (e.g., CEE, 2005). The key feature that differentiates our model from the literature is that the technology used in production is endogenous. In particular, we introduce two mechanisms that cause endogenous upgrades in the productivity of the production processes. First, R&D activities lead to the development of new technologies. Second, firms can affect the speed of diffusion of new technology by

affecting the flow of resources devoted to adopt new technologies. These two margins, introduce new state variables that define the state of technology and that affect the dynamics of the economy.

3.1 Households

Households consume final output, C_t, supply labor, L_t, save by increasing their riskless deposits in financial institutions, B_t , pay lump-sum taxes, T_t, and receive the profits accrued by the different companies in the economy, Π_t. unless otherwise noted, all quantities are expressed in real terms and prices are denoted in terms of aggregate output which is the numeraire in the economy.

Households solve the following problem

$$\max E_t \left[\sum_{i=0}^{\infty} \beta^i b_{t+i} \left[\ln \left(C_{t+i} - hC_{t+i-1} \right) - \frac{\psi}{1+\varphi} L_{t+i}^{1+\varphi} \right] \right] \tag{1}$$

subject to

$$C_t = W_t L_t + \Pi_t + T_t + R_t^f B_t - B_{t-1} \tag{2}$$

where $0 < \beta < 1$, $0 < h < 1$, $\psi, \varphi > 0$ and b_{t+i} is a shock to the households' discount factor that evolves stochastically following an AR(1) process. W_t is the wage rate and R_t^f is the gross return on riskless bonds. Households take both as given. As in CEE, we allow for external habit formation to capture consumption dynamics.

Let υ_t be the marginal utility of consumption

$$\upsilon_t = \left(C_t - hC_{t-1} \right)^{-1} \tag{3}$$

and $\Lambda_{t,t+1}$ be the marginal rate of substitution between consumption at t and $t+1$:

$$\Lambda_{t,t+1} \equiv \frac{\upsilon_{t+1}}{\upsilon_t} \tag{4}$$

The first order conditions that characterize the household problem are:

$$W_t \upsilon_t = \psi L_t^{\varphi} \tag{5}$$

and

$$E_t \left[\beta \Lambda_{t,t+1} R_{t+1}^f \right] = 1 \tag{6}$$

3.2 Credit spreads

Competitive financial intermediaries borrow funds from households at the rate R^f_{t+1} and lend it to the firms in the economy at rate R_{t+1}. We assume there is an exogenous and time varying intermediation cost Ω_{t+1}. This intermediation wedge is a shortcut for the financial frictions in the economy (e.g., Kiyotaky and Moore, Bernanke and Gertler, Bernanke, Gertler and Gilgricht, 1999, Gertler and Karadi,2011).In particular, $\log(\Omega_t)$ evolves stochastically following an AR(1) process.

Arbitrage pins down the lending rate, R_t :

$$E_t\left(\beta\Lambda_{t,t+1}(R^f_{t+1} * \Omega_{t+1})\right) = E_t\left(\beta\Lambda_{t,t+1}R_{t+1}\right) \tag{7}$$

3.3 Technology

The efficiency of production depends on exogenous productivity shocks and on the number of "adopted" intermediate goods in the production of capital, A^k_t, and final output, A^y_t. We characterize next the process that governs the evolution of these variables.

New intermediate goods

Prototypes of new intermediate goods are the result of R&D activities. R&D involves the investment of final output by innovators who have access to the following linear technology

$$Z^s_{t+1} = (\bar{\chi}_{st}S^s_t + 1)\phi Z^s_t, \tag{8}$$

where Z^s_t denotes the total number of prototypes developed in sector s (for $s = \{k, y\}$), S^s_t the total R&D expenditures, $\bar{\chi}_s$ is the productivity of R&D investments and ϕ denotes the probability that a previously developed prototype does not become obsolete in a given quarter. Though, innovators perceive the technology as linear, we allow for aggregate congestion in R&D expenditures by assuming that

$$\bar{\chi}_{st} = \frac{(S^s_t)^{\rho-1}}{(o^s_t)^{\rho}}, \tag{9}$$

where $\rho \in (0, 1]$, and o^s_t is a scaling factor to be defined below.

Let j^s_t denote the value of a newly developed prototype and let R_t be the interest rate at which innovators can borrow to finance their R&D investments. Then, free

entry into R&D implies that

$$1 = E_t \left[R_{t+1}^{-1} \phi \bar{\chi}_{st} Z_t^s j_{t+1}^s \right]. \tag{10}$$

Adoption (Conversion of Z to A)

Before a newly developed technologies can be commercialized and used in production, they need to be adopted. Potential adoption firms competitively bid for the right to adopt each intermediate good. These firms are owned by households. The adoption process involves a costly (stochastic) investment by adopters. In particular, an adopting firm that spends h_t^s units of final output at time t, will make a prototype usable for production at time $t+1$ with probability

$$\lambda_t^s = \lambda(\Gamma_t^s h_t^s) \tag{11}$$

with $\lambda' > 0$, $\lambda'' < 0$, and where Γ_t is a factor that is exogenous to the firm, given by

$$\Gamma_t^s = A_t^s / o_t^s. \tag{12}$$

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.

Once adoption has been successfully completed, the adopter can sell the adopted intermediate good in the market as a monopolist. Note that under this setup there is slow diffusion of new technologies on average (as they are slow on average to become usable). In addition, aggregation is simple since, once a technology is in use, all producers have access to it. As we show below, this formulation is also consistent with the evidence that the speed of diffusion of technologies is strongly pro-cyclical (e.g. Comin, 2009).

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 commercializing the technology. Profits π_t^s arise from the monopolistic power of the producer of the new good. Accordingly, we can express v_t^s as

$$v_t^s = \pi_t^s + \phi E_t \left[R_{t+1}^{-1} v_{t+1}^s \right]. \tag{13}$$

If an adopter is unsuccessful in the current period, he may try again in the subsequent periods to make the technology usable. Now we are in a position to define the

value of a prototype that has not been adopted yet, j_t^s. Intuitively, j_t^s is the value of the option to adopt the prototype. Formally, it is defined by the following Bellman equation:

$$j_t^s = \max_{h_t^s} -h_t^s + E_t\{R_{t+1}^{-1}\phi[\lambda_t^s v_{t+1}^s + (1-\lambda_t^s)j_{t+1}^s]\} \tag{14}$$

Optimal investment in adopting a new technology is given by:

$$1 = E_t\left[R_{t+1}^{-1}\phi\Gamma_t\lambda^{s\prime}\left(\Gamma_t^s h_t^s\right)\left(v_{t+1}^s - j_{t+1}^s\right)\right] \tag{15}$$

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, and in particular on the age of the un-adopted prototype. Thus, in equilibrium, the success probability is the same for all firms attempting adoption.

3.4 Production

The production side of the economy has two sectors that produce, respectively, final output and capital. The productivity of the production processes is largely determined by the range of intermediate goods available for production. In addition, we introduce nominal rigidities by imposing optimal Calvo pricing rules in the output sector and adjustment costs to the flow of investment for newly produced capital (e.g. CEE, 2005).

Output

Intermediate goods producers .– The A_t^y adopters that own the rights to commerzialize intermediate goods in the output sector, can produce copies of their prototype with the following production function:

$$Y_t(s) = x_t^y K_t(s)^\alpha \left(L_t(s)\right)^{1-\alpha} \tag{16}$$

where $Y_t(s)$ is the number of copies produced by the s intermediate good producer in the output sector, $K_t(s)$ and $L_t(s)$ are the amount of capital and labor she rents/hires, and x_t^y is the exogenous level of productivity. We assume that the (log) exogenous productivity in sector s evolves stochastically following an AR(1) process.

Cost minimization yields the following input demands:

$$\alpha \frac{Y_t(s)}{K_t(s)} = \bar{\eta}_t^{-1}[D_t + \delta P_{t+1}^I] \tag{17}$$

$$(1-\alpha)\frac{Y_t(s)}{L_t(s)} = \bar{\eta}_t^{-1} W_t \tag{18}$$

where D_t denotes the net rental rate of capital, δ the depreciation rate and P_{t+1}^I the price of installed capital, and $\bar{\eta}_t$

$$\bar{\eta}_t = (x_t^y)^{-1} \left(\frac{D_t + \delta P_{t+1}^I}{\alpha}\right)^{\alpha} \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}.$$

is the marginal cost of production of intermediate good producers.

Retailers .– There is a continuum (of mass one) of retailers. Each retailer produces one differentiated retail output, $Y_t(j)$, by aggregating the A_t^y available intermediate goods as follows:

$$Y_t(j) = \left(\int_0^{A_t^y} \left(Y_t^j(s)\right)^{1/\theta} ds\right)^{\theta}, \tag{19}$$

where $Y_t^j(s)$ denotes the demand of the j^{th} retailer of the s^{th} intermediate good.

Given the constant elasticity of substitution between intermediate goods in (19), intermediate goods producers find optimal to set a price equal to a constant markup θ times their marginal cost of production $\bar{\eta}_t$. Note that this means that all intermediate goods producers charge the same price. As a result, the marginal cost of producing one unit of retail output is:

$$\begin{aligned} \eta_t &= \theta \left(A_t^y\right)^{-(\theta-1)} \bar{\eta}_t \\ &= \frac{\theta}{\left(A_t^y\right)^{(\theta-1)} x_t^y} \left(\frac{D_t + \delta P_{t+1}^I}{\alpha}\right)^{\alpha} \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha} \end{aligned} \tag{20}$$

where $(A_t^y)^{(\theta-1)}$ reflects the efficiency gains from increases in the number of adopted intermediate goods, and x_t^y the effect of exogenous productivity.

Final output .– A continuum of competitive firms aggregate retail outputs to produce final output, Y_t, using the following production function:

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{1}{\mu_{pt}}} dj\right)^{\mu_{pt}} \text{ where } \mu_{pt} > 1. \tag{21}$$

The degree of differentiation between the retail outputs can be measured by $log(\mu_{pt})$, and evolves stochastically following an AR(1) process.

Cost minimization by producers of aggregate output yields the following demand schedule faced by retailers:

$$Y_t(j) = (\frac{P_t(j)}{P_t})^{\frac{-\mu_{pt}}{\mu_{pt}-1}} Y_t \tag{22}$$

where the P_t is the price index of final output:

$$P_t = \left(\int_0^1 P_t(j)^{-\frac{1}{\mu_{pt}-1}} dj \right)^{-(\mu_{pt}-1)}. \tag{23}$$

Nominal Rigidities

The producers of differentiated outputs set nominal prices on a staggered basis. As in SW and JPT, every period a fraction $1-\xi$ of final output firms are free to optimally reset their respective price. The remaining fraction ξ adjust their price according to a simple indexing rule based on lagged inflation. Let $P_t(j)$ be the nominal price of firm $j's$ output, and $\pi_t = P_t/P_{t-1}$ the inflation rate. Then, the indexing rule is given by:

$$P_{t+1}(j) = P_t(j) \left(\pi_t\right)^{\iota_p} \left(\pi\right)^{1-\iota_p} \tag{24}$$

where π is the steady state rate of inflation and ι_p 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.

$$E_t \sum_{s=0}^{\infty} \xi^s \beta^s \Lambda_{t,s} \{ [\frac{P_t^*}{P_{t+s}} \left(\prod_{j=1}^{s} \left(\pi_{t+j-1}\right)^{\iota_p} \left(\pi\right)^{1-\iota_p} \right) - \eta_{t+s}] Y_{t+s}(j) \} \tag{25}$$

given the demand function for firm j's product (22) and the marginal cost (20).

This yields the following expression for the optimal reset price:

$$0 = E_t \left\{ \sum_{s=0}^{\infty} \xi^s \beta^s \Lambda_{t,s} \left[\frac{P_t^*}{P_{t+s}} \left(\prod_{j=1}^{s} \left(\pi_{t+j-1}\right)^{\iota_p} \left(\pi\right)^{1-\iota_p} \right) - \mu \eta_{t+s} \right] Y_{t+s}(j) \right\} \tag{26}$$

From the law of large numbers, the price level evolves according to

$$P_t = [(1-\xi)(P_t^*)^{\frac{\mu-1}{\mu}} + \xi((\pi_{t-1})^{\iota_p} \left(\pi\right)^{1-\iota_p} P_{t-1})^{\frac{\mu-1}{\mu}}]^{\frac{\mu}{\mu-1}} \tag{27}$$

Capital

Investment .– For simplicity, we assume that the production of intermediate goods in the capital goods sector is linear in final output.[10] It takes $1/x_t^k$ units of aggregate output to produce one unit of capital intermediate good, where $\log(x_t^k)$ evolves stochastically following an AR(1) process. Investment, I_t^g, is produced competitively by combining intermediate capital goods with the following CES production function

$$I_t^g = \left(\int_0^{A_t^k} I_t(r)^{\frac{1}{\theta}} dr \right)^{\theta}, \text{ with } \theta > 1 \tag{28}$$

where $I_t(r)$ is the number of units of the r^{th} intermediate capital good used to produce investment.

Given the constant elasticity of substitution across intermediate goods, intermediate capital goods producers optimally charge a constant markup θ over the marginal cost of production $(1/x_t^k)$ for their intermediate goods. This pricing rule and the production function (28) imply that the price of a unit of investment, P_t^k, is

$$P_t^k = \left(\int_0^{A_t^k} \left(p_{it}^k\right)^{-\frac{1}{\theta-1}} di \right)^{\theta-1} = \frac{\theta \left(A_t^k\right)^{-(\theta-1)}}{x_t^k}, \tag{29}$$

where the term $\left(A_t^k\right)^{-(\theta-1)}$ reflects the efficiency gains from using a larger number of technologies in the production of investment.

Installing capital .– Investment needs to be installed before it adds to the capital stock used in production. A continuum (of mass one) of competitive firms install capital in factories. They buy investment at price P_t^k and sell installed capital at price P_t^I. Let $I_t = I_t^g - \delta K_t$ denote net investment in the economy. Capital installers maximize the present discounted value of installing capital taking as given the sequence of $\{P_t^k,\ P_t^I\}$:

$$\max_{\{I_\tau\}} E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} \Lambda_{t,\tau} \left[\left(P_\tau^I - P_\tau^k\right) I_t - f\left(\frac{I_t}{I_{t-1}\left(1+g_K\right)} \right) I_t \right] \tag{30}$$

where g_K is the growth rate of capital in the balanced growth path, and the function $f(.)$ satisfies the following properties: $f(1) = f'(1) = 0$, and $f''(1) > 0$. (See CEE, 1995.)

[10] The assymetry in the production of output and investment is convenient to simplify the structure of production. Comin and Gertler (2006) use a completely symmetric structure which delivers very similar results.

The sequence of optimal investment flows satisfy the following equation:

$$\begin{aligned} P_t^I &= P_t^K + f\left(\frac{I_t}{I_{t-1}(1+g_K)}\right) + f'\left(\frac{I_t}{I_{t-1}(1+g_K)}\right)\frac{I_t}{I_{t-1}(1+g_K)} \\ &\quad -E_t\left[\beta\Lambda_{t,t+1}f'\left(\frac{I_{t+1}}{I_t(1+g_K)}\right)\left(\frac{I_{t+1}}{I_t(1+g_K)}\right)^2\right]. \end{aligned}$$

The resulting law of motion for the capital stock is as follows:

$$K_{t+1} = K_t + I_t\left(1 - f\left(\frac{I_t}{I_{t-1}(1+g_K)}\right)\right). \tag{31}$$

3.5 Policy

Fiscal .– The government finances a stochastic flow of expenditures, G_t, with lump sum taxes, T_t, levied on households. We assume that it runs a balanced budget. That is,

$$G_t = T_t, \text{ for all } t. \tag{32}$$

We assume that G_t evolves stochastically following an AR(1) process with drift, where the drift grows at the same rate as the economy along the balanced growth path.

Monetary .– Monetary policy is characterized by a Taylor rule with interest-rate smoothing. Let i_t be the gross nominal interest rate, i its steady state value, η_t is the marginal cost and $\hat{\eta}_t$ is marginal cost along the deterministic balanced growth path. Then

$$\frac{i_t}{i} = \left(\frac{i_{t-1}}{i}\right)^{\rho_r}\left(\left(\frac{\pi_t}{\pi}\right)^{\phi_p}\left(\frac{\eta_t}{\hat{\eta}_t}\right)^{\phi_y}\right)^{1-\rho_r}\exp(\mu_{m,t}) \tag{33}$$

where $\mu_{m,t}$ is an exogenous shock to the policy rule that follows an AR(1) process.

The connection between nominal and interest rates is determined by the following Fisher equation:

$$i_t = R_{t+1}^f E_t \pi_{t+1}$$

3.6 Aggregate Resource constraint

The resource constraint of the economy is as follows:

$$Y_t = C_t + G_t + \frac{P_t^k I_t}{\theta} + \sum_{s\in\{y,k\}} h_t^s(Z_t^s - A_t^s) + \sum_{s\in\{y,k\}} S_t^s \tag{34}$$

In equilibrium, aggregate output is equal to

$$Y_t = \frac{1}{\Delta_t} x_t^y \left(A_t^y\right)^{\theta-1} K_t^{\alpha} L_t^{1-\alpha} \tag{35}$$

where Δ_t is an inefficiency wedge due to relative price dispersion which drops in first order approximations.[11]

4 Estimation

We estimate the model using quarterly data from 1984:I to 2008:III on seven variables in the US economy which are the data counterpart to the growth rates of output, consumption, real investment, hours worked, inflation, nominal risk-free interest rates, and the spread between borrowing and lending rates.[12] We do not data beyond 2008:III in the estimation of the structural parameters because the Taylor rule may have been binding. However, we use data until 2012:IV to identify the shocks that have hit the economy.

The model contains seven structural shocks: the household's subjective discount factor, b_{t+i}, government consumption, G_t, shocks to the monetary policy rule, μ_{mpt}, the shock to the differentiation of the retail outputs, μ_t^p, [13] the exogenous component of TFP, x_t^y, the exogenous component of the cost of producing investment goods, x_t^k, and shocks to the spread between the borrowing and lending rates, Ω_t.

We calibrate some parameters associated with the endogenous technology processes using micro-estimates from the productivity literature (See appendix). As it is standard in quantitative macroeconomics (e.g., AS, 2007) we estimate the rest of the

[11] In particular,

$$\Delta_t = \int_0^1 \left(\frac{P_t(j)}{P_t}\right)^{-\frac{\mu}{\mu-1}} dj. \tag{36}$$

[12] The Appendix describes the sources and transformations of the data used in the estimation.

[13] This shock is isomorphic to a cost-push shock in the Philip's curve.

parameters of the model using Bayesian techniques. For comparison purposes we also estimate a version of our model where technology is exogenous. That is, the rate of development and adoption of intermediate goods in both sectors is fixed at the steady state values and the only stochastic variation in productivity is due to the shocks to the exogenous technology variables (x_t^s). Otherwise, the exogenous technology model has the same frictions as our baseline model (price rigidities, habit formation and adjustment costs to investment).

4.1 Priors and posterior estimates

Table 3a presents the prior distributions for the structural estimates along with the posterior estimates. Table 3b presents the same information for 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 SW (2007), PST (2006) and JPT (2010).

The estimates we obtain are close to those in the literature (as well as to the exogenous technology version of our model). In particular, this is the case for the parameters in the Taylor rule (1.52 for the coefficient on inflation and 0.069 for the coefficient on the marginal cost), the elasticity of the costs of adjusting the investment flows (0.43) and the implied labor supply elasticity ($1/\varphi$ =1.69). One parameter which is slightly higher than the micro evidence is the implied average time that a price is fixed is just over a year ($1/(1-\xi) = 4.75$ quarters). However, this estimate is reasonable given that our model does not include wage rigidities. Finally, we obtain an estimate of the elasticity of adoption with respect to adoption expenditures equal to 0.57. This seems to us a conservative value given that the range of elasticities of innovating with respect to R&D expenditures in the literature is higher and that the empirical evidence suggests that adoption rates vary at least as much over the cycle as innovation activity (Comin, 2009). The estimates of the parameters that characterize the stochastic processes are reported in Table 3b. The autocorrelation of the credit shock is 0.91 and it is driven by the persistence in the credit spread measure from GZ (2012).

4.2 Impulse response functions

Next, we analyze the impulse responses using the estimated model. We start with the credit shock. Figure 3a presents the results for our model (solid line) and for the version with exogenous technology (dashed line).[14] In response to a shock that increases upon impact by one percentage point the spread betwen the borrowing and lending rate, output drops initially approximately 0.8% (panel 1). After the initial impact, output slightly recovers but after six quarters starts to decline again. The impact of teh shcok on output clearly outlasts the shock. While the shock has virtually disappeared after 15 quarters, 20 quarters after the shock, output is still 0.9% below trend.

In contrast, the same credit shock generates an initial output contraction of only .3% in the economy with exogenous technology. Since prices are fixed in the short term, output is demand determined and the initial drop in output reflects a drop in aggregate demand. Therefore, the source of the larger output drop in the model with endogenous technology is the larger fall in aggregate demand. To see this, note that consumption does not fall in either model upon impact (panel 3). Investment drops more in the model with exogenous technology (panel 2) – as we show below investment is too volatile in the model with exogenous technology; but adoption and R&D expenditures drop significantly when we allow them to respond to business cycle conditions (as we discuss below). The response of the investments in technology improvement amplifies aggregate demand fluctuations, leading to a larger initial output response. Since capital and TFP are fixed in the short run, the endogenous technology model produces the larger reduction in output with a larger drop in hours worked (panel 4).

The credit shock affects the return to adoption and R&D investments through two distinct channels. First, as with other recessionary shocks, the reduction in aggregate demand affects the flow of profits accrued by intermediate goods producers. Second, increases in the credit spread raise the discount factor at which firms discount future profits resulting in a lower present discounted value of profits, for a given profit stream. Both of these mechanisms reduce the values of adopted (panel 9) and un-

[14] For comparability purposes, the impulse response for the exogenous model are computed using the parameter estimates of the endogenous model.

adopted technologies, v^s and j^s, leading to a drop in R&D investments (panel 6) and the rate of adoption of intermediate goods (panel 7). Interestingly, the second channel (i.e., the discount rate channel) applies only to credit disruptions.[15] Since the first channel affects similarly all shocks, it follows that credit shocks lead to larger fluctuations in the endogenous component of technology than the other shocks.

The fluctuations in adoption and R&D investments have transitory effects in the growth rate of TFP and embodied productivity but very protracted effects on their levels. To see this, recall that the (log) of TFP and the (log) of the price of investment in our model are given by the following expressions:

$$\ln(TFP_t) = \overbrace{\ln\left(x_t^y\right)}^{\text{Exogenous}} + \overbrace{(\theta-1)\left\{\ln(A_t^y)+\hat{\alpha}\ln(A_t^k)\right\}}^{\text{Endogenous}} \tag{37}$$

$$-\ln(P_t^k) = \overbrace{\ln\left(x_t^k\right)}^{\text{Exogenous}} + \overbrace{(\theta-1)\ln(A_t^k)}^{\text{Endogenous}} \tag{38}$$

Both of these variables have an exogenous component and an endogenous one that depends on the range of adopted technologies.[16] A reduction in the adoption rate in the investment sector leads to a gradual increase in the cost of producing capital goods as measured by P^k (red, dashed line in panel 5). Similarly, transitory reductions in the growth of intermediate goods or in the speed of adoption eventually lead to permanent reductions in the level of adopted intermediate goods (panel 8) and, hence, in TFP. This is why the credit shock has a more persistent effect on the output level in the model with endogenous technology, despite the smaller fluctuations in the capital stock.

The estimated model not only delivers a plausible response to the credit, but also to the other shocks. Figures 3b-3f display the impulse response functions to the shocks to

[15] Figure A1 illustrates the importance of the discount rate channel. In particular, it plots the impulse response to a credit shock in a model where the value of adopted and un-adopted technologies is not discounted by the borrowing rate but by the lending rate. The recession generated by credit shocks in this model is significantly smaller than in our baseline model.

[16] The third term in the TFP expression reflects the productivity in the capital goods sector that is not fully measured by the investment price indeces. $\hat{\alpha}$ equals the capital share (α) times the fraction of productivity gains in the capital goods sector that are unmeasured by the BEA. One way to calibrate that share is by comparing the rate of decline of the BEA investment deflators and the quality adjusted price indeces of Gordon, Cummins and Violante.

TFP, the price of investment, the price markup, monetary policy and to government spending. These shocks also lead to pro-cyclical responses of investment, and expenditures in R&D and adoption. As in Gali (1999), the TFP shock leads to an initial contraction of hours worked caused by the rigidity of prices which prevents firms to pass their efficiency gains to the consumers in the form of lower prices, and therefore pushes firms to reduce their labor demand in order to meet the production needs. For the other shocks, hours worked are strongly pro-cyclical. As with the credit shock, the endogenous technology mechanisms help both in the amplification and propagation of shocks. The pro-cyclicality of adoption and R&D expenditures amplifies fluctuations in aggregate demand. Furthermore, they also generate persistent fluctuations in the new state variables that characterize the endogenous technology of the economy, A_t^s and Z_t^s. However, these effects are smaller for non-credit than for credit shocks because non-credit shocks do not afect the rate at which companies discount technology improvement investments.

4.3 Theoretical moments and model fit

Tables 4a and 4b present the theoretical standard deviations of the growth rates and HP-filtered levels of key macro variables in the models with endogenous and exogenous technology. Overall, our model does a decent (but far from perfect) job. Both models struggle to match the volatility when the variables are measured in growth rates, and our model does a better job when exploring the volatility of HP-filtered levels. We find that reassuring since the main focus of this paper is in the propagation of business cycle shocks.

In Table 4a, we observe that our model produces a mean standard deviation for the growth rate of the key observables that is higher than in the data. The margins of discrepancy range from 17% for output growth to 82% for the growth in hours worked.[17] Though randomness in the realization of shocks and uncertainty over the structural parameters lead to non-trivial confidence intervals around the theoretical volatilities in the model, the data counterparts are always outside the 95% confidence intervals. The model with exogenous technology does a better job than our model in

[17] We measure the margins of discrepancies as the logarithm of the ratio of the mean standard deviation in the model to the standard deviation in the data for the period 1984:I-2008:III..

matching the empirical volatility of output and hours growth, but it does worse for the growth rate of consumption and, especially, investment.

The model does a much better job in replicating the observed volatility of the HP-levels of the variables (Table 4b). In particular, it closely matches the volatility of output (1.23 vs. 1.25 in the data). For investment and consumption the average standard deviation is close to the empirical counterpart which falls within the 95% confidence interval. For hours worked, the average volatility in the model is 1.84 vs. 1.44 in the data which falls outside the 95% confidence interval by little. When comparing our model with the exogenous technology version, ours does a better job at matching the empirical HP-filtered volatility of output, consumption and investment and it does worse for hours worked.

An alternative way to compare the model fit in both models is through their marginal log-likelihoods. Table 5a shows that the marginal likelihood for our baseline model is significantly higher than in the formulation with exogenous technology (-725 vs. -780).

4.4 Variance decomposition

To assess the importance of each shock for business cycle fluctuations, we conduct the unconditional variance decomposition for the growth rates (Table 5a) and the HP-filtered levels (Table 5b) of output, consumption, investment and hours worked.

The shock that causes largest fluctuations in output growth is the government spending shock which accounts for 46% of its variance. This shock should not be taken literally as innovations to government spending but as a proxy for exogenous shifts in aggregate demand. Other significant shocks for output growth fluctuations are the credit shock (21%), and the shock to monetary policy (18%) while shocks to exogenous productivity in the output and capital sector account for approximately 5% of the variance of output growth each.

The most significant shock for fluctuations in consumption growth is the time-preference shock (51% of its variance). For investment growth it is the shock to the exogenous productivity in the capital sector which is responsible for 66% of the variance and for hours growth the most significant source of fluctuations is the shock to government spending (40% of the variance). The credit shock is also a significant

driver of fluctuations in the growth of these three variables contributing, approximately, to 16% of their variance.

The variance decomposition differs significantly if we use the model with exogenous technology (see bottom panel of Table 5a). In particular, the contribution of the credit shock for fluctuations in the growth rates of output, consumption and hours worked are much smaller than in our model (3% vs. 21% for output, 2% vs. 16% for consumption and 2% vs. 17% for hours worked).[18] In contrast, the shocks to the time-preference, government spending and exogenous productivity in the output sector tend to account for a larger share of the variance in first differences. For example, government spending shocks account for 59% of the variance of output growth (vs. 46% in our model); shocks to the time preference for 71% of the variance of consumption growth (vs. 51% in our model); and TFP shocks for 35% of the variance of hours growth (vs. 20% in our model).

The significance of the shocks under the endogenous technology model is also quite sensitive to the frequency we consider. Table 5b presents the variance decomposition for HP-filtered levels. For example, the government spending shock which accounts for 46% of the variance of output growth only accounts for 21% of the variance of HP-filtered output. Instead, the credit shock is the main driver of HP-filtered output –accounting for 50% of its variance, vs. 21% for output growth. Credit shocks also are the main driver of fluctuations in consumption (50%), investment (47%) and hours worked (41%).

The increase in the importance of credit shocks for HP-filtered levels than for growth rates reflects the larger effect that credit shocks have on R&D and technology adoption investments. As a result, credit shocks lead to larger fluctuations in the stock of adopted intermediate goods (in both sectors) which drive fluctuations at lower frequencies.[19] To illustrate this logic, note that once we shut down the endogenous technology mechanisms (bottom panel of Table 5b), credit shocks are no longer very significant in fluctuations in HP-filtered levels. In particular, the governemnt spending shock accounts for a large majority in HP-filtered output, consumption and

[18] Monetary policy shocks also tend to account for a smaller fraction of fluctuations in teh model with exogenous technology.

[19] This conclusion would hold a fortiori if we conducted a variance decomposition at lower than business-cycle frequencies.

hours under the exogenous technology model. Therefore, our main take away from these decompositions is that, at lower frequencies, credit shocks become a large driver of fluctuations because they lead to large fluctuations in the endogenous components of productivity. Interestingly, we do not need to go to very low frequency for these effects to affect significantly economic fluctuations. Table 5b shows that endogenous technology upgrading mechanisms are important at conventional business cycle frequencies.

5 Analysis

After estimating the model and studying its theoretical properties, we use it to shed light on the U.S. business cycle history between 1984:I and 2012:IV. To this end, we conduct three distinct exercises. We start with a historical decomposition of output growth that helps us assess the historical significance of each of shocks in the U.S. business cycles. Then, we explore the endogenous technology mechanisms in output fluctuations. In our second exercise, we analyze the endogenous components of TFP and embodied productivity resulting from our model with the data counterparts. Finally, we study what role the endogenous components of TFP and embodied productivity played in the evolution of key macro variables. To this end, we conduct a counterfactual where we feed in the estimated shocks (from our model) into a model where technology is exogenous and compare the resulting macro series with the actual data.

5.1 Historical decomposition

Figure 4a presents seven panels each plotting the contribution to output growth of each of the shocks. As a way of comparison, Figure 4b presents the same decomposition for the model with exogenous technology.

Credit disturbances have not played a major role in the business cycle fluctuations of the 1980s and 1990s. Credit spreads barely increased in 1990 during the first recession in our sample (see Figure 1). During the second half of the 1990s, they remained low but according to our model did not add much to the economic expansion. They increased more significantly in 2000 and in 2002, but do not seem to have

contributed much to the 2001 recession. However, since 2002, credit conditions have become critical to understand business cycles in the U.S. The easing of credit conditions after 2002 contributed to the expansion that followed the 2001 recession. Most importantly, the dramatic deterioration of credit markets, reflected in the increase in spreads since 2007, was the key driver of the Great Recession. In particular, the credit shock is responsible for much of the decline in output growth until 2009, for the initial stabilization in 2009, and for the slow subsequent recovery. It is apparent from Figure 4a that had the credit shock been the only disturbance in the economy, the post-recession recovery would have been faster. However, it is also clear from the historical decomposition that the evolution of credit markets was an important determinant of GDP growth in the post-recession period. As we shall show below, credit conditions not only affected the evolution of the economy at the high frequency. They were key drivers of lower frequency fluctuations in the production potential of the economy after the Great Recession.

The shock to government spending, which captures short-run fluctuations in aggregate demand, also plays a significant role in business cycle fluctuations. Fluctuations in aggregate demand played a significant role in the 80s output expansion, in the 1990 recession, in the expansion during the second half of the 90s, the 2001 recession and the 2000s expansion. However, they do seem to have played a relatively smaller role in the Great Recession, where they only seem to matter after the second quarter of 2009.

Other shocks that play a role during the Great Recession are the price mark-up and the monetary policy shocks. The price mark-up is isomorphic to a labor supply shock, and captures the low frequency contraction of labor supply in the U.S. (REF) which accelerated during the Great Recession. The initial easing of the Federal Reserve helped mitigate the contraction, but this effect stopped when interest rates hit the zero-lower-bound. At this point, our model interprets the deviations of actual interest rates from the Taylor rule as positive innovations to monetary policy that further contract the economy. The historical decomposition also reveals that monetary policy shocks also accomodated the recessionary episodes in 1990 and 2001.

The historical decomposition assigns a role for TFP shocks in the recessions and recoveries of 1990, 2001 and 2008. This surely reflects cyclical variation in capacity utilization rather than variation in fundamental technology (e.g., Burnside, Eichem-

baum, Rebelo, 1995). Shocks to the price of investment and to the household's discount factor do not play a prominent in the business fluctuations observed during the 1984-2012 period.

The account of U.S. business cycles that emerges from the exogenous technology model is very different from our model's (see Figure 4b). For example, the increase in credit spreads has a smaller impact in the economy when endogenous technology mechanisms are absent. Instead, the output contraction during the Great Recession is driven evenly by virtually all shocks. Most shocks also seem to play a role in the other two recessions that occurred during our period of interest. However, in those the government spending shock played a predominant role. This alternative account of recent U.S. business cycle history seems to us less plausible than the account that emerges from our model. Hence, we conclude that endogenizing the firms' technology improvement investments is important to obtain a proper understanding of the sources of business cycle fluctuations.

5.2 Evolution of R&D and productivity

Evolution of R&D .– To assess the plausibility of the firm's response to economic conditions, we compare the evolution of (linearly) detrended real R&D expenditures in the model with the actual evolution in the data (Figure 5a). The series implied by the model follow relatively closely the data (the correlation between the two series is 0.4). In both series there was a decline in real R&D expenditures in the 1980s, a recovery after the 1990 recession, that eventually led to a peak towards the end of the twentieth century. The key difference with respect to the timing is that while the global maximum in the data is at the peak of the dot-com bubble in 2000, the peak in R&D implied by our model is in 2004. After the peak, both in data and model there is a steep decline that accelerates during the financial crisis. In particular, between 2007 and 2009, (detrended) R&D expenditures drop by 17% in model and by 15% in data. After that, the two series differ somewhat in the magnitude of the recovery in R&D. While in the model, there is a steep recovery of about 11%, in the data, the recovery is much milder (approximately 2%).

In addition to the slight discrepancies in the timing of R&D fluctuations in the model and the data, there is also a difference in the amplitude of fluctuations. R&D

is more volatile in the data than in our model. In particular the standard deviation is 10% in the data vs. 6.5% in the model.[20] This difference in volatility proves that the magnitude of the fluctuations in the resources devoted by firms to upgrade the technology in our model is not unreasonably high in the light of the data.[21]

Evolution of TFP .– Figure 5b compares the evolution of the endogenous component of TFP in our model with the capacity-adjusted TFP series for the business sector (Fernald, 2012). The standard deviation of the endogenous component of TFP is half that of total TFP (1.1% vs. 2%). The correlation between the two series for the full sample is .55. Both the endogenous component of TFP and capacity-corrected TFP fall between 1988 and 1992, and start a protracted increase since then. In the model, the endogenous component of TFP reaches a maximum around 2000. Between the minimum in 1992:III and the maximum in 2000:III the endogenous component of TFP increases by 2.7%. This is comparable to the increase in capacity-adjusted TFP in the data between the minimum in 1992:I and the level during 2000. After the dot-com peak, capacity-adjusted TFP continued to increase until 2005, at which point it started to decline. The endogenous component of TFP, instead, slightly declined during the 2001 recession and recovered afterwards to come back to its maximum level in 2007:II. At this point, both series intersect and co-move downwards again. The endogenous component of TFP declines monotonically by 4.3% since then until 2012:IV. At this point it reaches the global minimum in our sample at -2.9% below trend. The decline of TFP in the data is not monotonic but the overall drop during this same period is of 3.8%. This account of the evolution of TFP shows that the endogenous development and adoption of TFP has been the critical driver of the gradual deterioration of TFP in the U.S. economy over and after the Great Recession.

Evolution of embodied productivity .– In a two-sector like ours, endogenous variation in embodied productivity will affect the firms incentives to accumulate physical capital. Therefore, it is instructive to explore the series of embodied productivity

[20] The differential in volatility is smaller with respect to the NSF measure of R&D that has a standard deviation of 6.7%.

[21] It is not clear whether when inquired by COMPUSTAT or by the NSF, firms report pure R&D expenditures or whether they also include in their expenses adoption investments. To consider this scenario, we have compared the evolution of total adoption and R&D expenditures implied by our model. The resulting series is very similar to the series of R&D. The correlation between the two is .97, and its standard deviation is .

produced in our model by the endogenous technology upgrading processes in the capital goods sector. In the data, embodied productivity is typically measured by the inverse of the relative price of equipment and software over the GDP deflator (e.g., Greenwood, Hercowitz and Krusell, 1997). This literature has used the fact that the deflator of structures grows approximately at the same rate as the GDP deflator to argue that the overwhelming majority of embodied productivity comes from equipment and software. Since, in our model, we have calibrated the long-run rate of embodied productivity to match the rate of decline of the price of investment, we have to adjust the endogenous component of embodied productivity by the share of equipment and software, α_{eq}, as follows:[22]

$$\text{Endogenous embodied productivity}_t = \frac{(\theta - 1)\ln(A_t^k)}{\alpha_{eq}}.$$

Figure 5c plots the evolution of embodied productivity in the data and the endogenous component for the model. As with TFP, the endogenous component of embodied productivity fluctuates less than overall productivity. (The standard deviation of the endogenous component is 1.5% while for overall embodied productivity it is 3.2%.) The two series are highly correlated (0.86). In particular, both declined from the mid-80s to teh mid 90s, increased until the 2001 recession, and dropped precipitously during the Great Recession. The only period where the endogenous component and overall embodied productivity did not co-move is the period between the dot-com and the Great recessions.

The endogenous component of embodied productivity has contributed significantly to the deterioration of embodied prodictivity during the Great Recession. Between 2007:IV and 2012:IV, the endogenous component of embodied productivity has dropped by 5.4 percent, which represents a bit more than 50% of the overall drop in embodied productivity (9.8%).

5.3 Counterfactuals

To assess the relevance of the endogenous technology mechanisms we explore how the U.S. economy would have evolved if rather than adjusting technology to the business

[22] In the data, $\alpha_{eq} = .7$. Alternatively, we could have adjusted the inverse of the relative price of equipment by multiplying it by α_{eq}.

cycle conditions, firms let technology grow at the balanced growth rates. Specifically, we take the shocks series identified by the endogenous technology model, feed them to both models and compare the resulting evolution of five variables: output, TFP, hours worked, the price of invetsment and the capital stock. One way to interpret the exogenous technology series is that they are what an agent would expect if he observed the shocks identified by the endogenous technology model and used the model with exogenous technology to evaluate the effect of the shocks.

Figure 6 plots the results from this counterfactual exercise. In solid blue line it depicts the evolution of each variable under the endogenous technology model and in dashed red the evolution under exogenous technology. The endogenous technology mechanisms play a critical role both in amplifying and propagating business cycles. Detrended output (panel 1) is more volatile in the endogenous technology model than in the exogenous technology. The standard deviations of the series are 4.6% vs. 3.6%. For example, the peak for output around 2000 under endogenous is 3% higher than under exogenous technology. The larger volatility of output in the endogenous technology model is in part due to the fact that this model generates larger fluctuations at medium term frequencies (Comin and Gertler, 2006). For example, the output expansion that followed the 1991 recession and that peaked in the early 2000s is two percentage points larger when technology is endogenous.

As a result of the propagation and amplification introduced by the endogenous technology mechanisms, our model provides a different account of business cycle fluctuations even for a given set of shocks. The instance where this is most obvious is during the Great Recession. During the initial contraction phase, the reduction in adoption expenses caused a faster drop in output than in the exogenous technology model. More evidently, the pace of recovery differs markedly in the two models. An observer that used the model with exogenous technology to predict the evolution of detrended output would expect a strong recovery after 2009III and that by 2012IV the economy would be only 4% below trend. Instead, one that used our model would (correctly) expect the economy to be 8.6% below trend.

The other panels in Figure 6 help us understand the source of the divergence in output between the endogenous and exogenous technology output series. The second panel plots the resulting TFP series under endogenous and exogenous technology. The difference between the two series is therefore the evolution of the endogenous

component of TFP. Comparing panels 1 and 2 it is clear that much of the difference between the output series in the endogenous and exogenous technology models is due to the direct effect that the technology adoption mechanisms have on TFP.

The third panel shows a similar pattern for embodied productivity as measured by the inverse of the price of investment. The difference in dynamics for both embodied and disembodied productivity affects the evolution of both capital and hours worked. The fourth panel shows that hours worked also contributed to amplifying the gap in output between the two series during the 1990s expansion. Naturally, the higher productivity reached by the endogenous technology model by the end of the expansion, increased the marginal product of labor and led to a higher level of hours worked than in the exogenous technology model. In the fifth panel, we see that the capital stock for the endogenous technology series grew more during the 1990s expansion, and collapsed more precipitously during the great recession.

5.4 Decomposition of endogenous component of productivity

After showing the significance of the endogenous technology mechanisms in driving the fluctuations in key macro aggregates, we can wonder what role does each shock play in driving endogenous embodied and disembodied productivity. Figures 6a and 6b contains the contributions of the most significant shocks. The shocks to credit, price markup (or cost push), monetary policy and TFP contribute significantly to shaping the evolution of the endogenous component of both embodied and disembodied productivity. The first three shocks contribute to the 1990s expansion, the decline that followed the dot-com recession and especially to the sharp decline in productivity during and after the great recession. The credit shock caused the largest decline in endogenous TFP between 2007IV and 2012IV (-1.2%), followed by the cost push shock (-1.17%) and government spending (-1.1%). The TFP shock affected the dynamics of endogenous productivity in a distinct way to all the other shocks. In particular, it caused a drop in endogeous TFP until 2000, and an increase since then. The contributions to each of tehse shocks to the endogenous components of embodied productivity are quite similar.

6 Conclusions

Credit disruptions have been regarded as a significant source of business cycle fluctuations. The standard argument has been that they increase the cost of funds faced by companies when investing in physical capital. However, physical capital is not the only asset in which companies invest. Companies engage in innovation and technology adoption investments that affect the level of technology in the economy. In this paper, we have shown that these endogenous technology channels are critical both for the amplification and propagation of business cycle shocks.

In the context of the Great recession, we have found that increases in credit spreads account for the majority of the initial contraction in output and hours worked. This conclusion hinges importantly on the amplification of business fluctuations once we allow firms to endogenously upgrade technologies. Endogenous technology upgrading contributes critically to the presistence of business cycles. In particular, we find that the endogenous dynamics of productivity account for a majority of the decline in embodied and dismebodied productivity between 2007:IV and 2012:IV. Furthermore, the endogenous evolution of productivity is responsible for the slow recovery we have observed. In particular, had technology remained in the balanced growth path, by 2012IV, the economy would be only 4% below trend instead than the actual 8.6% below trend (that our model generates).

References

[1] Greenwood, J., Z. Hercowitz, and P. Krusell (1997), "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review* Vol. 87, n. 3: 342-362.

7 Appendix (not for publication)

7.1 Calibration

We begin with the standard parameters. A period in our model corresponds to a quarter. We set the discount factor β equal to 0.995, to match the steady state share of investment to output. Based on steady state evidence we also choose the following numbers: (the capital share) $\alpha = 0.35$; (government consumption to output) $G/Y = 0.2$; (the depreciation rate) $\delta = 0.015$; and (the steady state utilization rate) $U = 0.8$.[23] We set the inverse of the Frisch elasticity of labor supply ζ to 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 **?**, we fix the steady state gross valued added markup in the final output, μ, equal to 1.1 and the corresponding markup for the capital goods sector, μ^k, at 1.15.

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

The growth rate of GDP in steady state depends on the growth rate of capital and

[23] 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.

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 identify. 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 $\lambda^s(.)$ as follows:

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

These are $\bar{\lambda}^s$ and ρ_λ. To calibrate these parameters we try to assess the average adoption lag and the elasticity of adoption with respect to adoption investments. Estimating this elasticity is difficult because we do not have good measures of adoption expenditures, let alone adoption rates. One partial measure of adoption expenditures we do have is development costs incurred by manufacturing firms trying that make new capital goods usable, which is a subset of the overall measure of R&D that we used earlier. A simple regression of the rate of decline in the relative price of capital (the relevant measure of the adoption rate of new embodied technologies in the context of our model) on this measure of adoption costs and a constant yields an elasticity of 0.9. Admittedly, this estimate is crude, given that we do not control for other determinants of the changes in the relative price of capital. On the other hand, given the very high pro-cyclicality of the speed of adoption estimated by **?**, 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 $1/\lambda + 1/4$. **?** 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.[24] For these reasons, we set $\bar{\lambda}^s$ to match an average adoption lag of 5 years and a quarter.[25]

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.

7.2 Data

In our estimation, we use data on output (Y_t), consumption (C_t), real investment (I_t), hours worked (L_t), real risk-free interest rates (R_t^f), inflation (π_t), and the credit spread (R_t^p). Following SW(2007), PST (2006) and JPT (2010), all real quantities are scaled by the working age population (which come from the economic report of the president).[26] Output is real GDP from the BEA. Consumption corresponds to personal expenditures of non-durables and services, from the BEA. Investment includes durable consumption, and gross capital formation. Hours worked are measured by the total hours in the non-farm business sector from the BLS. The risk-free rate is measured by the Fed funds rate deflated by the growth rate of the GDP deflator. The credit spread is measured by the differential between the average yield on corporate bonds issued by publicly-traded U.S. corporations and the yield in 10-year U.S. government bonds. The data comes from Gilchrist and Zakrajsek (2012). Using these data, our observables are the following variables:

$$[\Delta logY_t \quad \Delta logC_t \quad \Delta logI_t \quad \Delta logL_t \quad R_t^f \quad \pi_t \quad R_t^p]$$

[24] **?** and **?**.

[25] It is important to note that, as shown in **?**, 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 **?** and others we are being conservative in showing the power of our mechanism.

[26] We log-linearly interpolate the annual series.

Figure 1: Spread between corporate bonds and 10-year government bonds

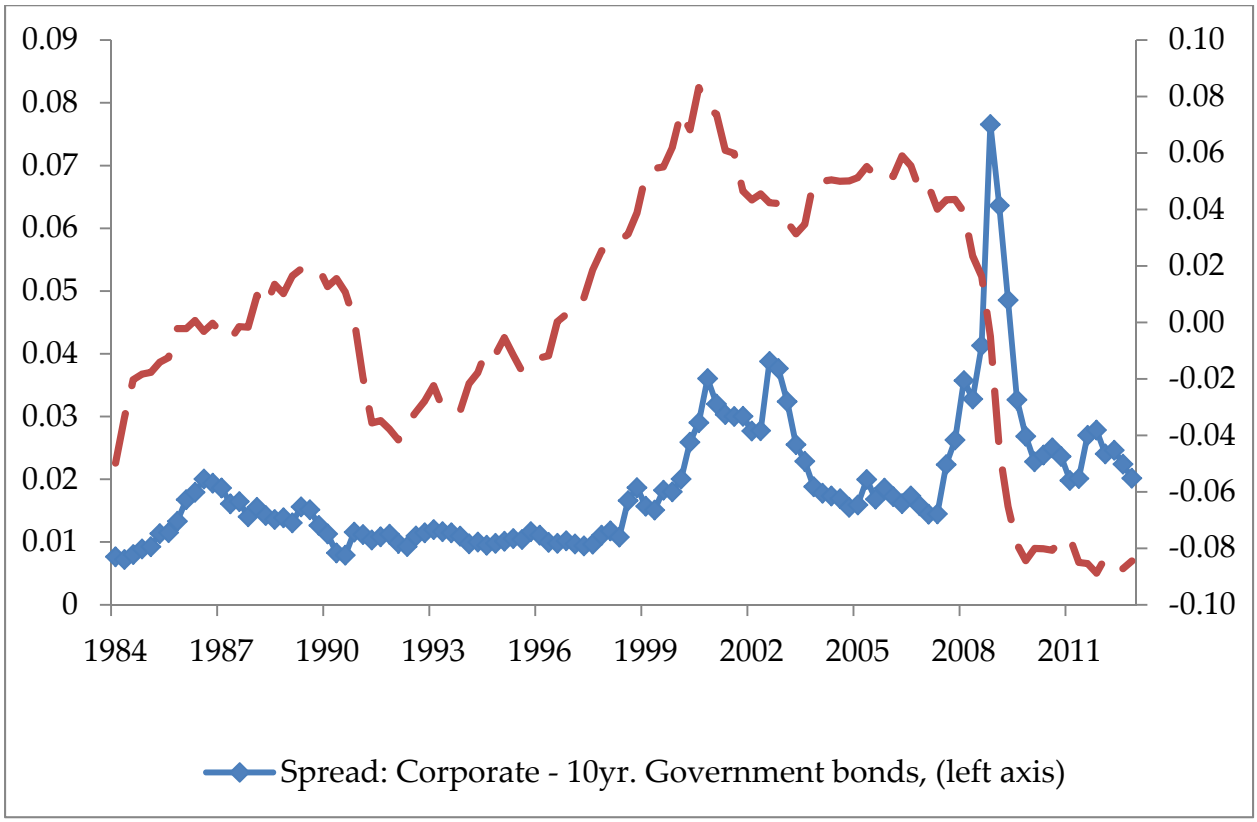


Figure 2a: Evolution of detrended R&D and equipment investment

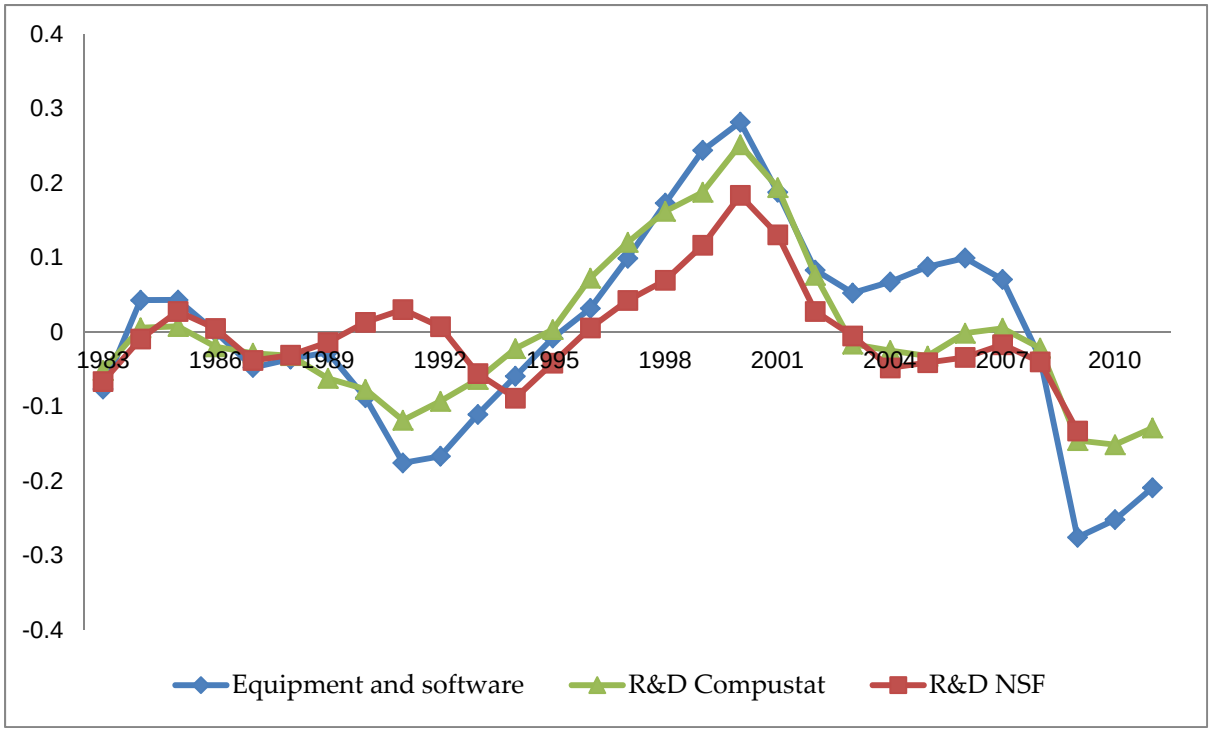


Table 2b: Evolution of detrended embodied and disembodied productivity

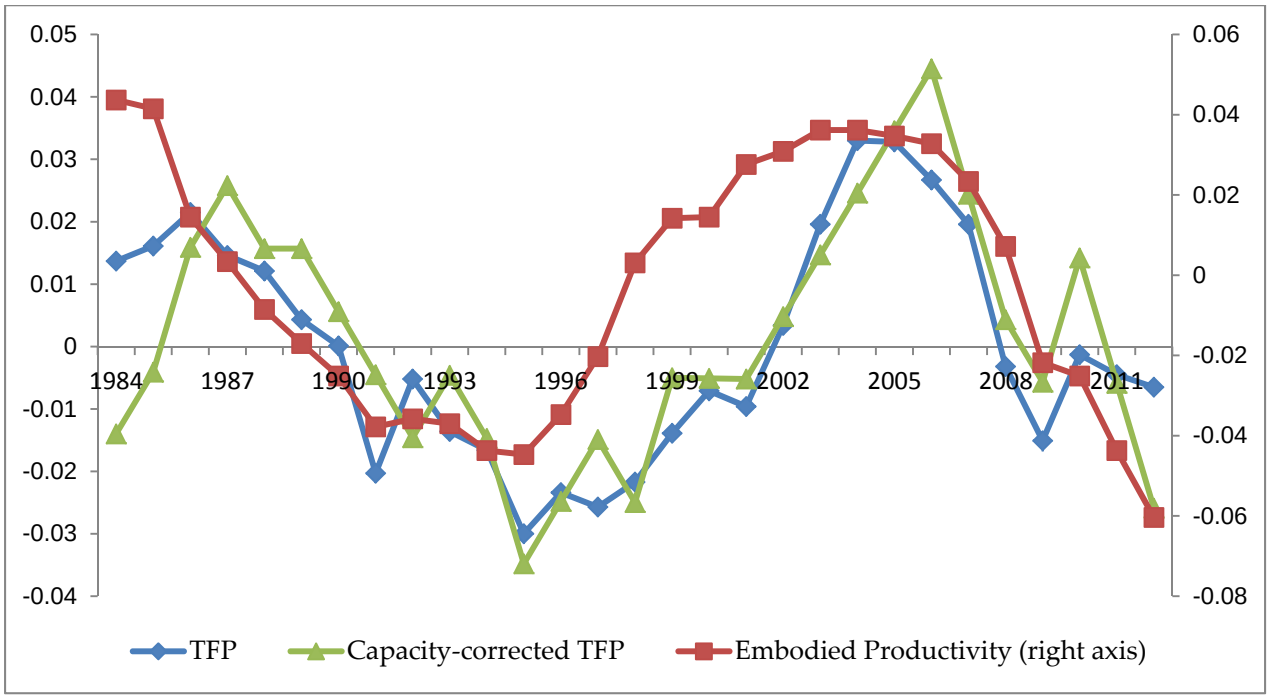
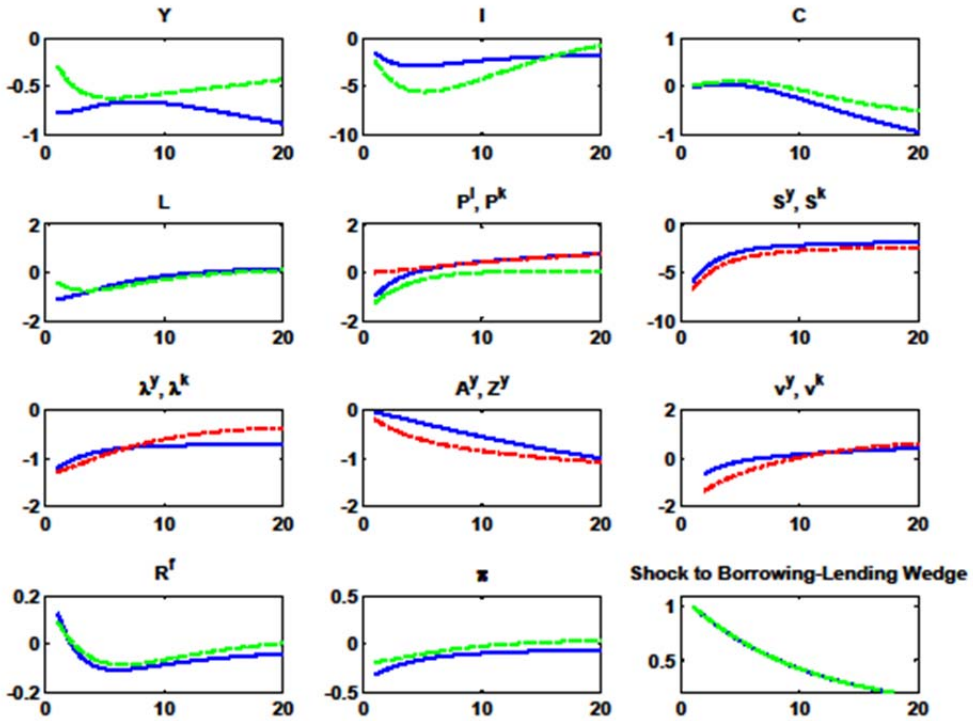
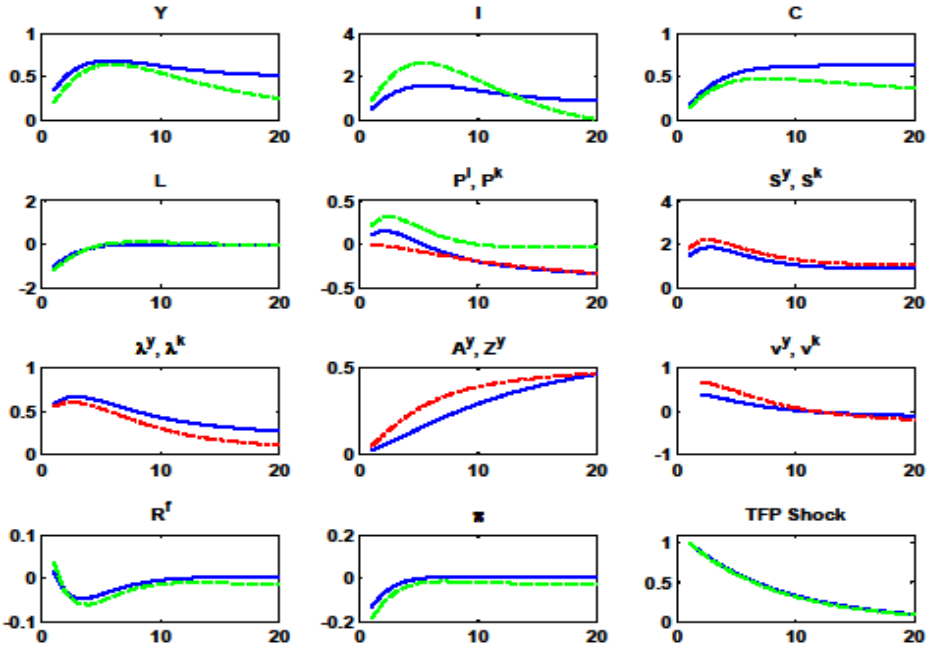


Figure 3a: Impulse response functions, credit shock



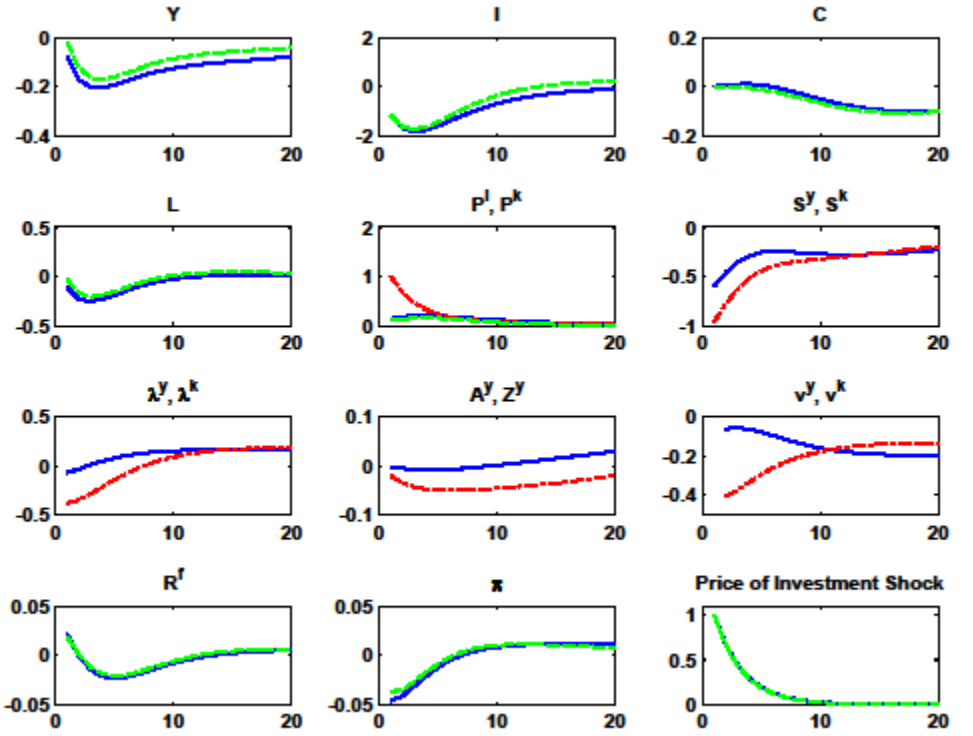
Notes: Blue solid line denotes endogenous model, green dashed line denotes exogenous model.
Red semi-dashed line denotes the second variable in the endogenous model: P^k, S^k, λ^k, Z^y and v^k.

Figure 3b: Impulse response functions, TFP shock



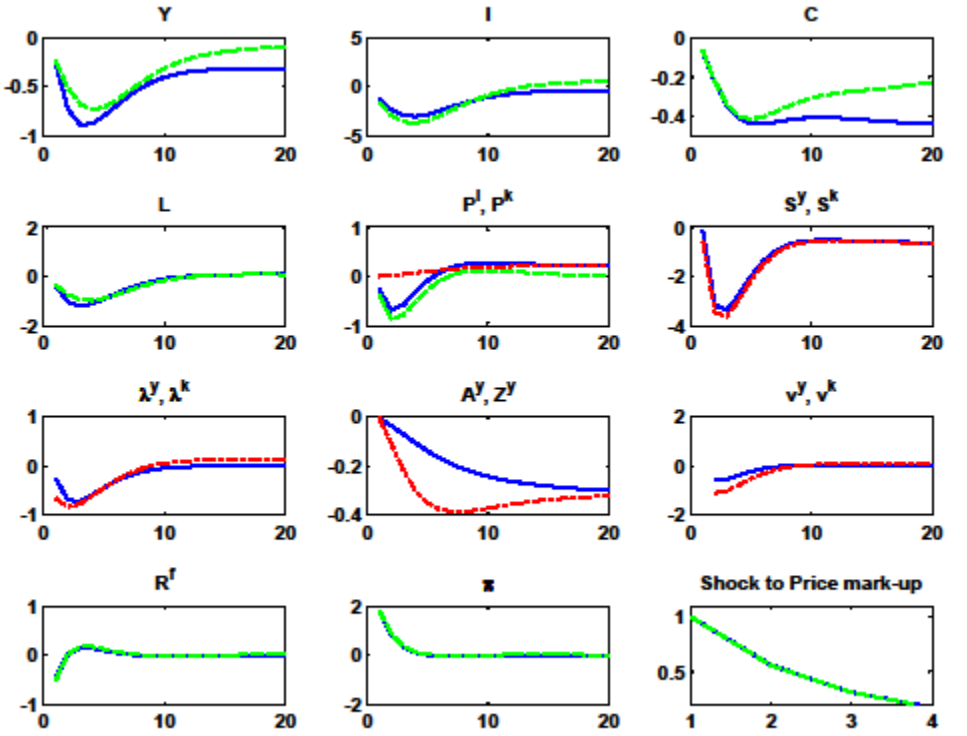
Notes: Blue solid line denotes endogenous model, green dashed line denotes exogenous model. Red semi-dashed line denotes the second variable in the endogenous model: P^k, s^k, λ^k, Z^y and v^k.

Figure 3c: Impulse response functions, price of investment shock



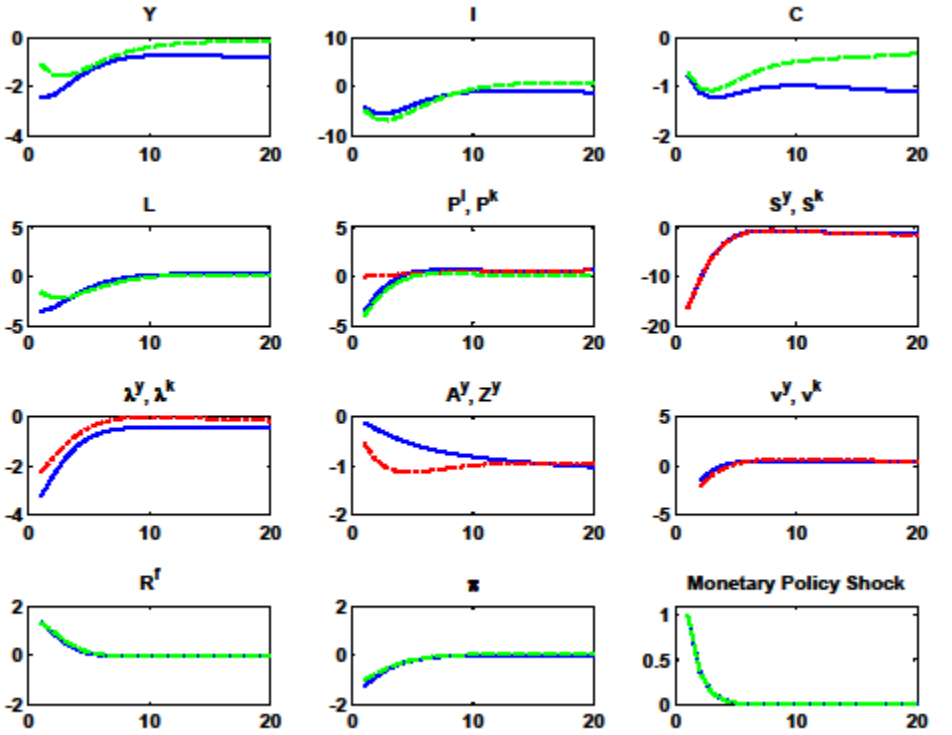
Notes: Blue solid line denotes endogenous model, green dashed line denotes exogenous model.
Red semi-dashed line denotes the second variable in the endogenous model: P^k, s^k, λ^k, Z^y and v^k.

Figure 3d: Impulse response functions, price markup shock



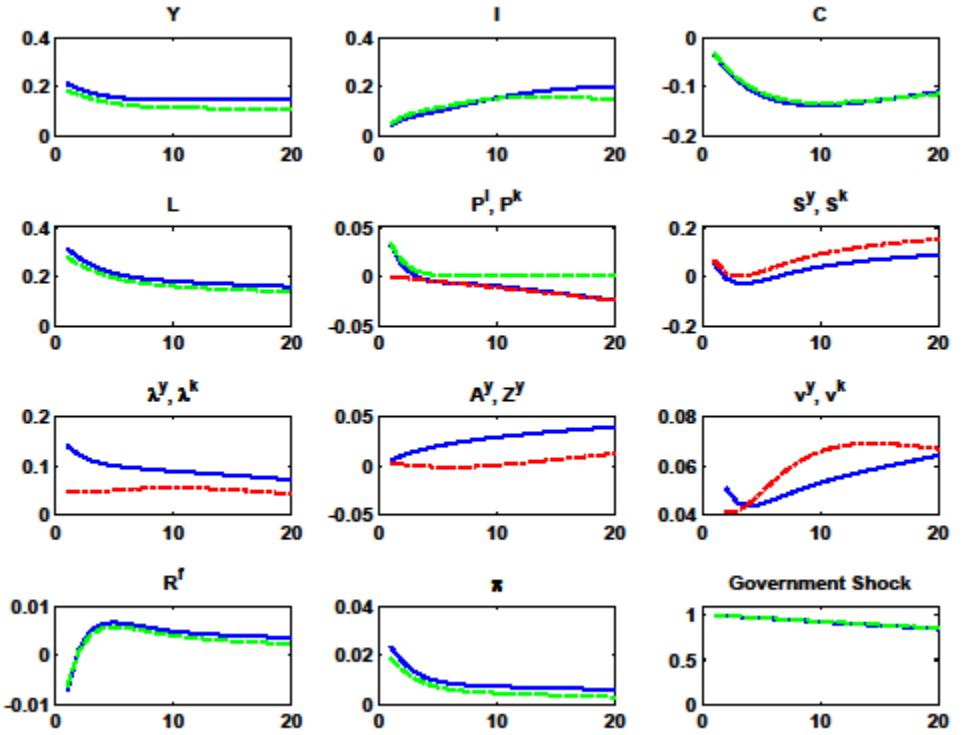
Notes: Blue solid line denotes endogenous model, green dashed line denotes exogenous model.
Red semi-dashed line denotes the second variable in the endogenous model: P^k, S^k, λ^k, Z^y and v^k.

Figure 3e: Impulse response functions, monetary policy shock



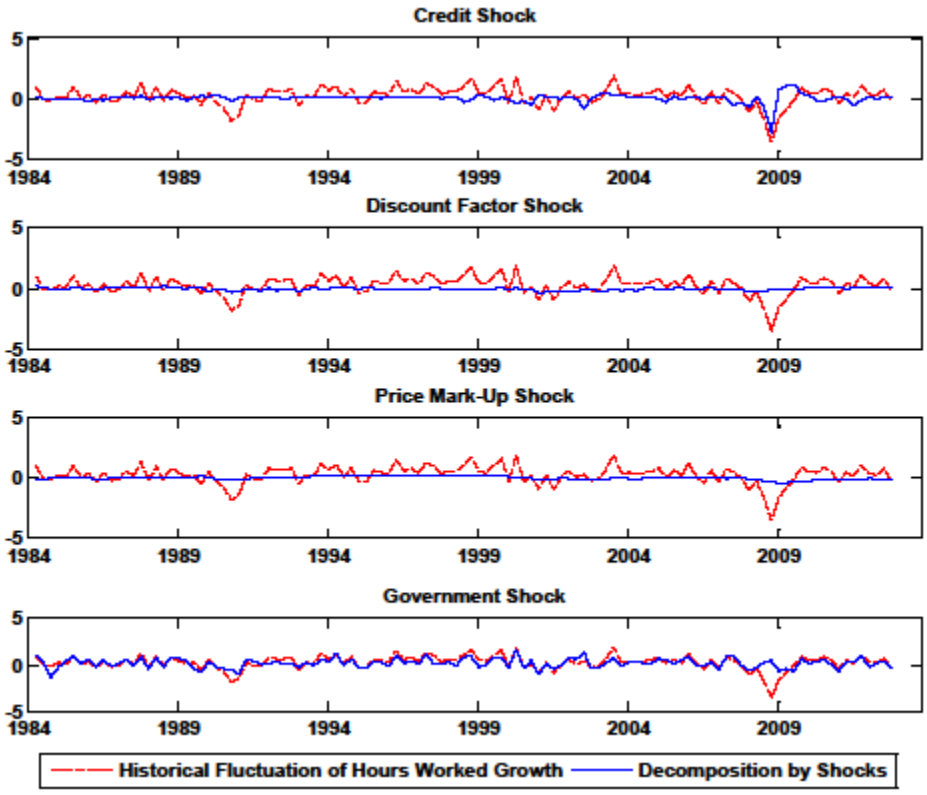
Notes: Blue solid line denotes endogenous model, green dashed line denotes exogenous model. Red semi-dashed line denotes the second variable in the endogenous model: P^k, S^k, λ^k, Z^y and v^k.

Figure 3f: Impulse response functions, government spending shock



Notes: Blue solid line denotes endogenous model, green dashed line denotes exogenous model.
Red semi-dashed line denotes the second variable in the endogenous model: P^k, S^k, λ^k, Z^y and v^k.

Figure 4a: Historical decomposition



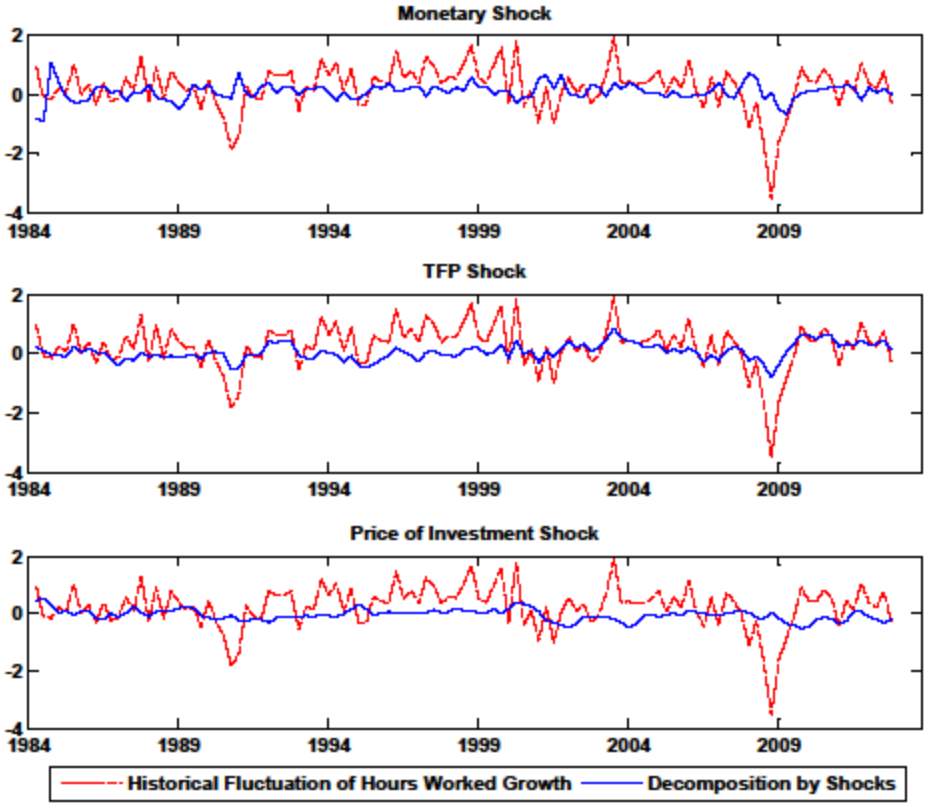

Monetary Shock
2
0
-2
-4
1984
1989
1994
1999
2004
2009
TFP Shock
2
0
-2
-4
1984
1989
1994
1999
2004
2009
Price of Investment Shock
2
0
-2
-4
1984
1989
1994
1999
2004
2009
Historical Fluctuation of Hours Worked Growth
Decomposition by Shocks

Figure 4b: Historical decomposition, Exogenous technology model

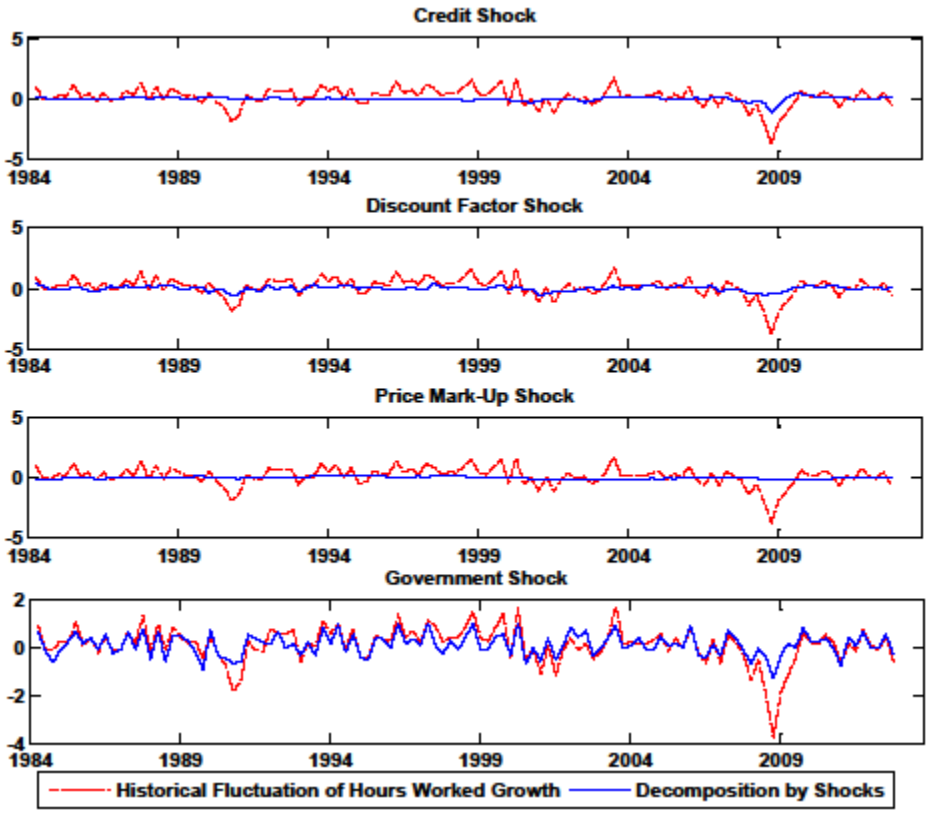


Figure 5a: Evolution of (detrended) R&D

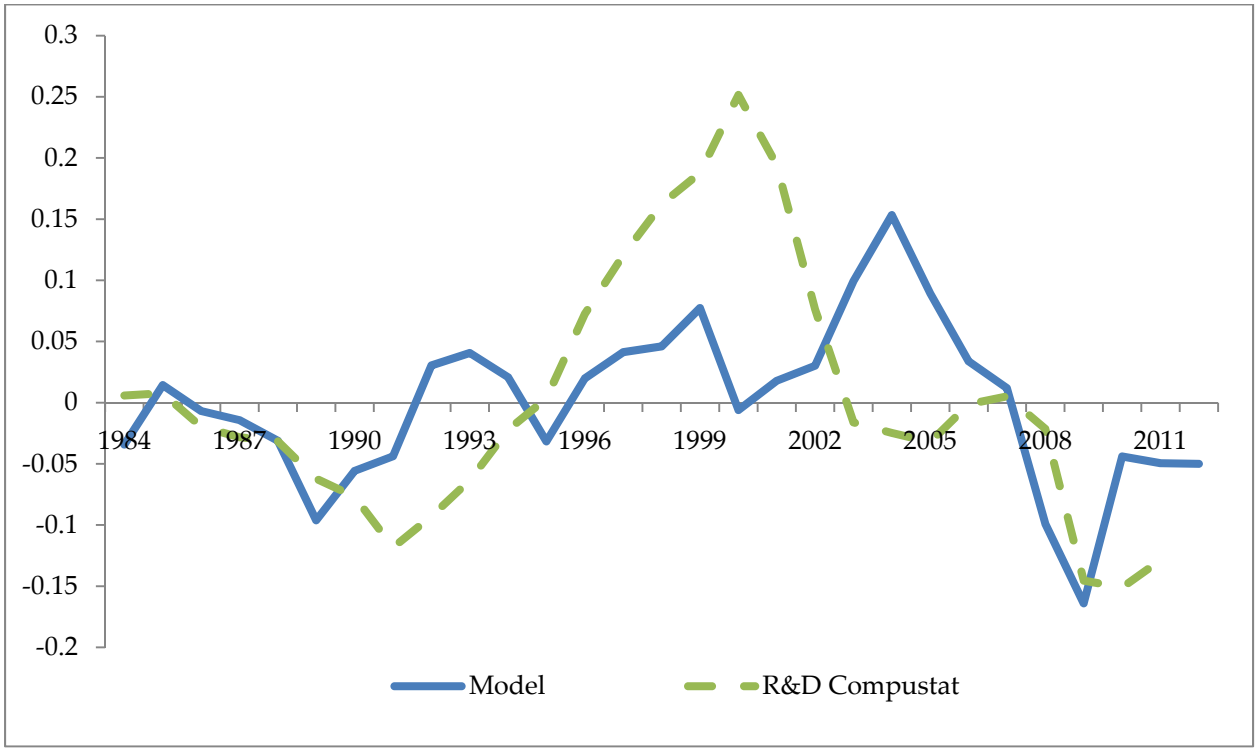


Figure 5b: Evolution of (capacity-corrected) TFP (data) and endogenous TFP (model)

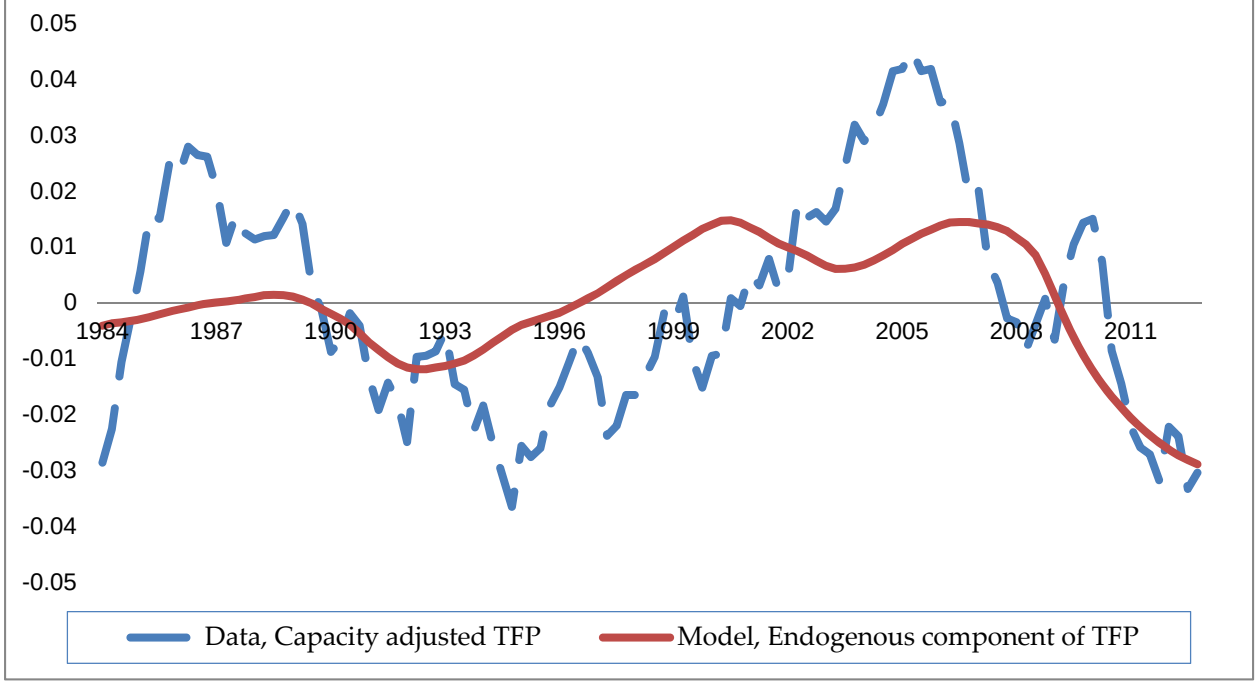


Figure 5c: Evolution of embodied productivity (data) and endogenous component (model)

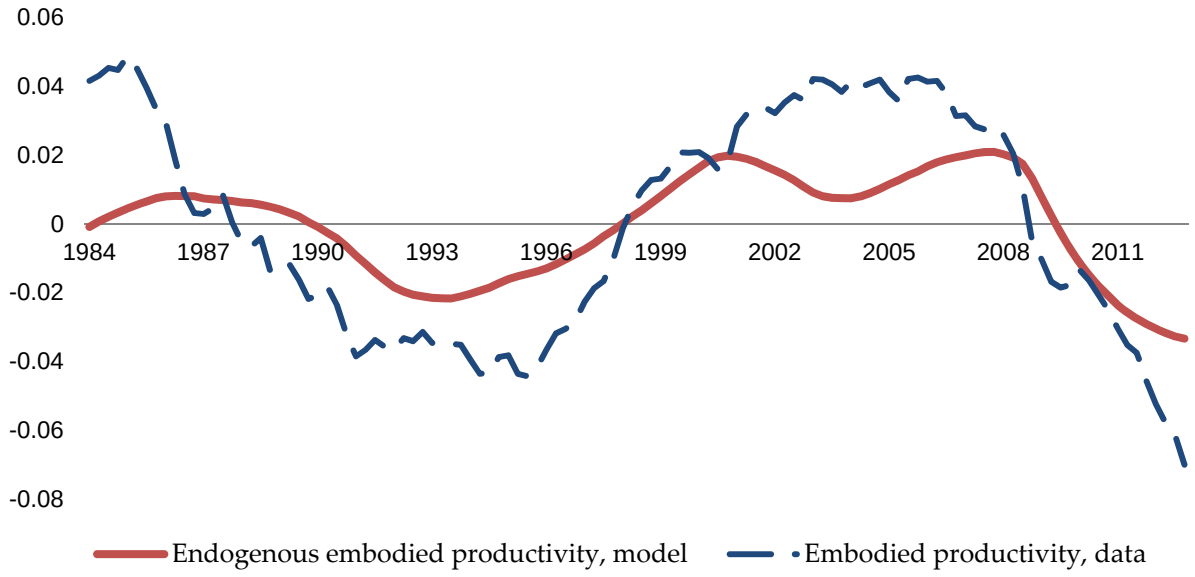
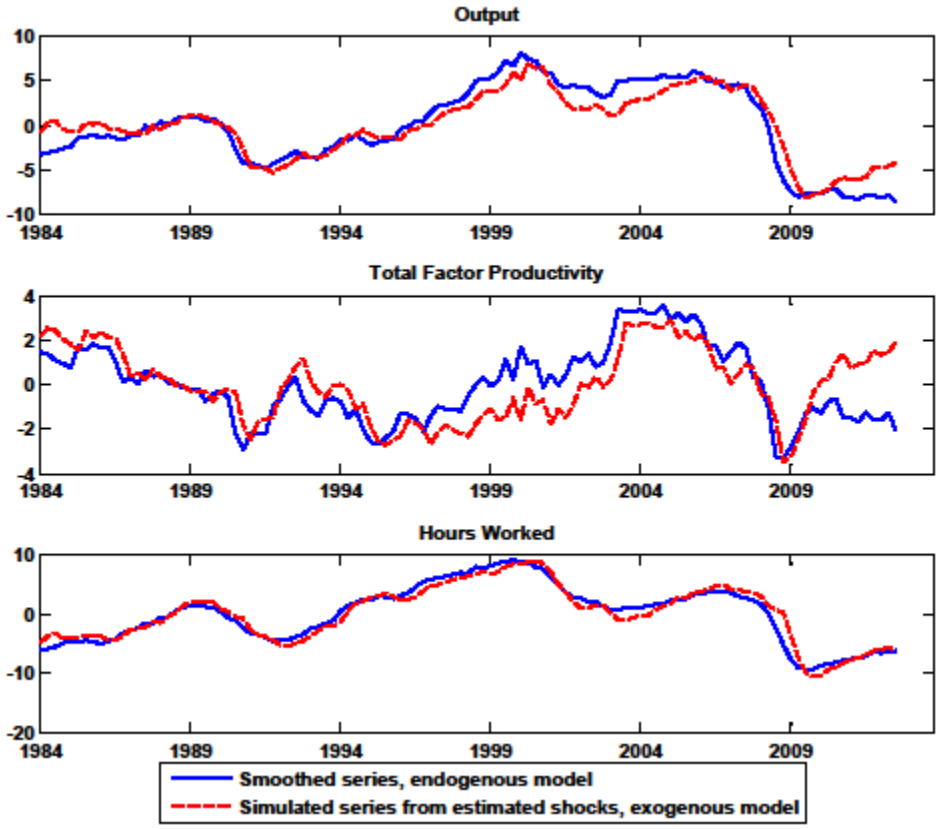


Figure 6: Evolution of economy after feeding endogenous technology shocks in endogenous and exogenous technology models.



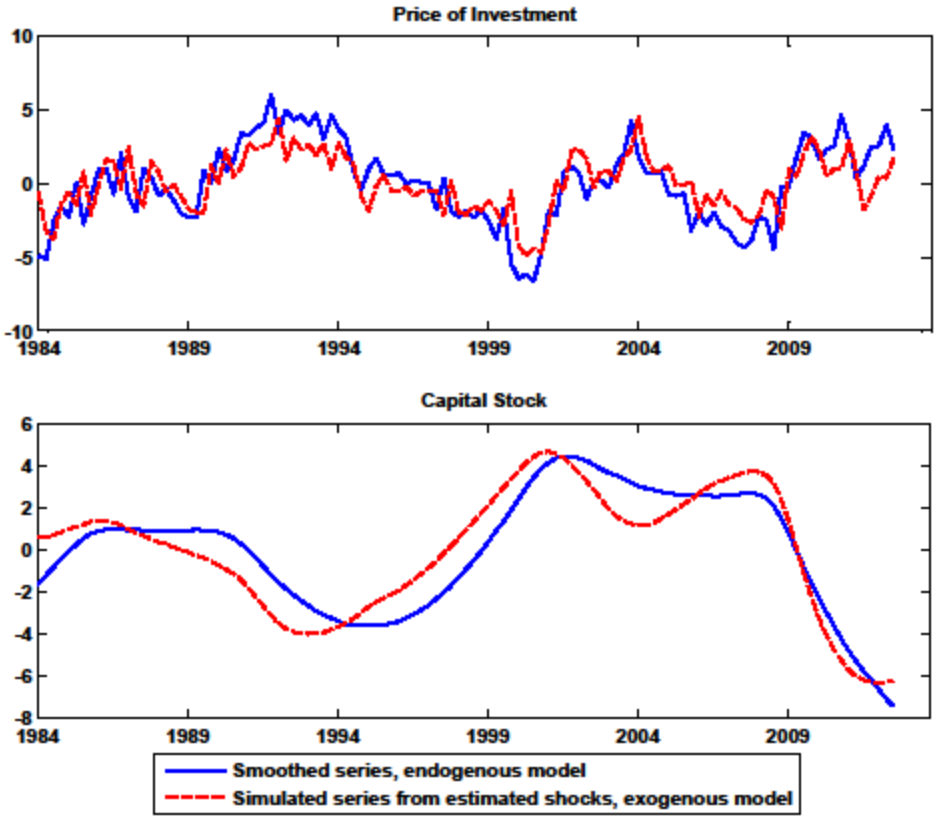

Price of Investment
10
5
0
-5
-10
1984
1989
1994
1999
2004
2009
Capital Stock
6
4
2
0
-2
-4
-6
-8
1984
1989
1994
1999
2004
2009
Smoothed series, endogenous model
Simulated series from estimated shocks, exogenous model

Figure 6a: Decomposition of endogenous TFP, key shocks

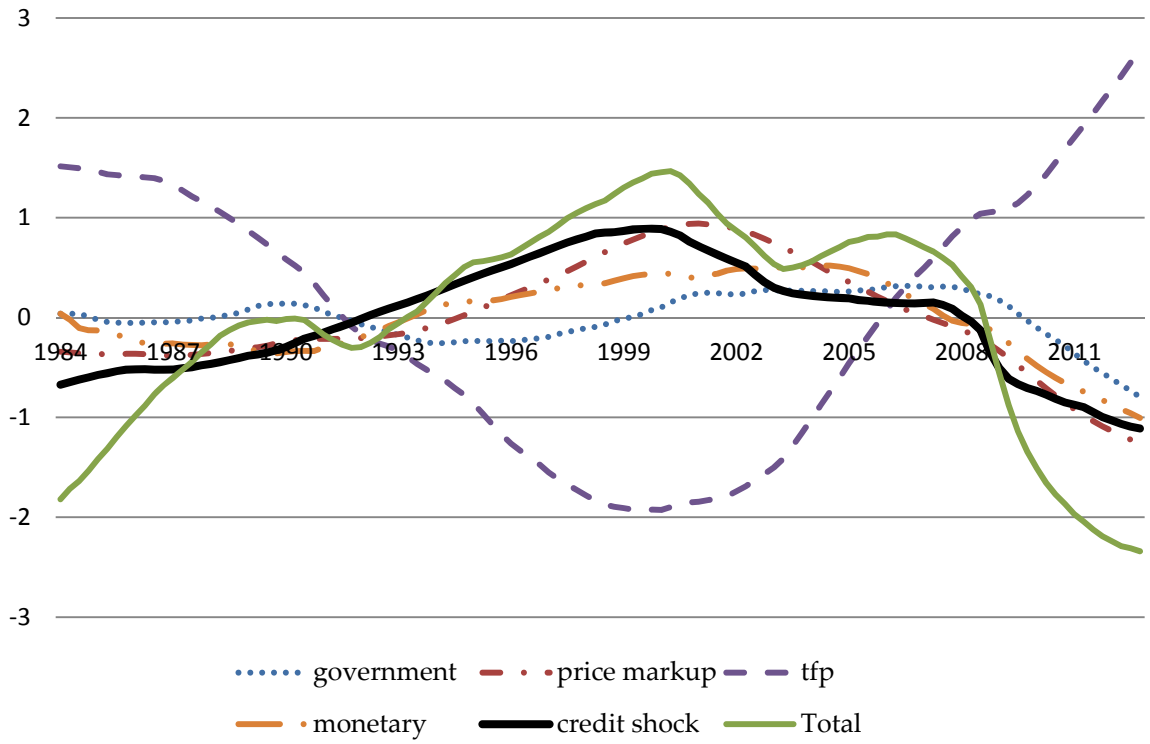


Figure 6b: Decomposition of endogenous component of embodied productivity

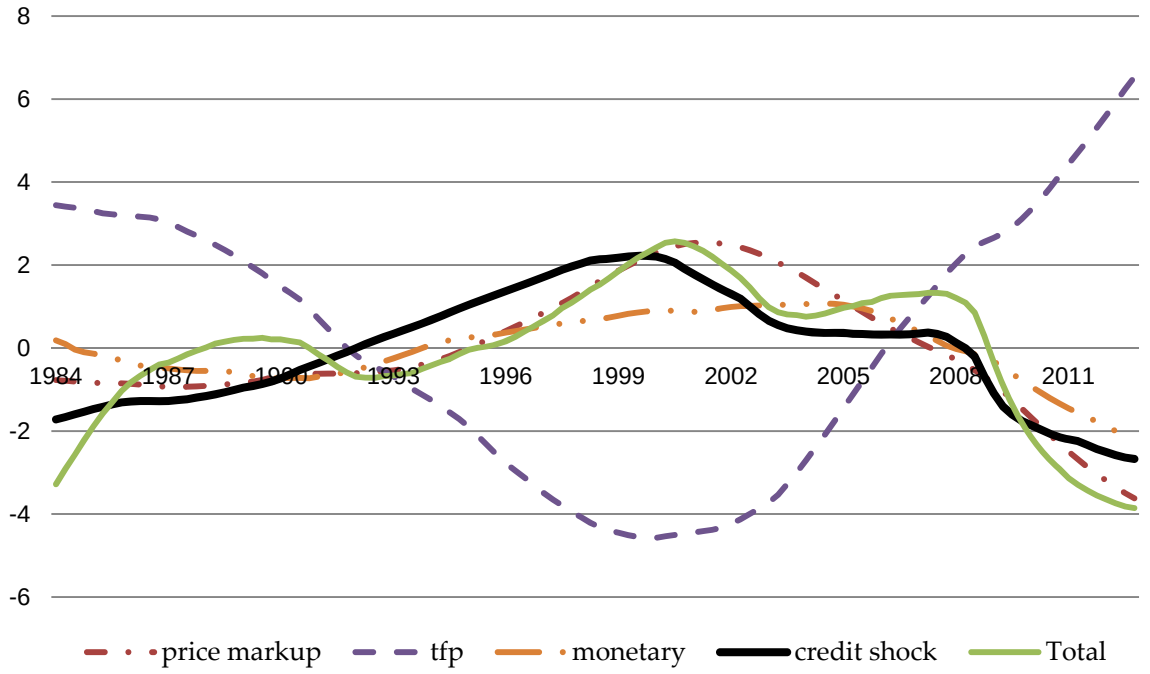


Table 1A: Cyclicality of R&D expenditures and equipment investment.

	GDP	
	Linear detrend	Band-Pass Filter
	1983-2011	1950-2011
R&D Compustat	0.73	0.46
R&D NSF*	0.65	0.38
Equipment and software	0.87	0.83

* Only goes until 2009

Table 1B: Co-movement between productivity and technology upgrade investments.*

	R&D Compustat			Equipment and Structures		
Lags of R&D and Investment	TFP	Capacity-corrected TFP	Embodied	TFP	Capacity-corrected TFP	Embodied
0	-0.20	-0.26	0.37	0.13	0.03	0.59
1	-0.11	-0.11	0.51	0.17	0.16	0.68
2	0.13	0.09	0.64	0.30	0.33	0.75
3	0.42	0.32	0.75	0.53	0.50	0.78
4	0.71	0.57	0.80	0.75	0.66	0.7

*Period: 1983-2011, Linearly detrended

Table 2A: Sectoral demand and corporate R&D expenditures during the Great Recession

	Real Value Added Growth in 3 digit Naics sector (2007-2011)				Real Gross Output Growth in 3 digit Naics sector (2007-2011)			
	I	II	III	IV	V	VI	VII	VII
Sectoral demand growth	0.189*** (0.03)	0.133*** (0.008)	0.074** (0.033)	0.086*** (0.009)	0.6*** (0.05)	0.5*** (0.02)	0.169** (0.084)	0.43*** (0.034)
N observations	12309	12309	12309	12309	12309	12309	12309	12309
N companies	3323	3323	3323	3323	3323	3323	3323	3323
Weighted	No	Yes	No	Yes	No	Yes	No	Yes
Year Dummies	No	No	Yes	Yes	No	No	Yes	Yes

All regressions include firm-fixed effects

Table 2B: Sectoral demand, credit constraints and corporate R&D expenditures during the Great Recession

	Real Value Added Growth in 3 digit Naics				Real Gross Output Growth in 3 digit Naics			
	I	II	III	IV	V	VI	VII	VII
Sectoral demand growth	0.187*** (0.03)	0.094*** (0.012)	0.077** (0.035)	0.053*** (0.013)	0.58** (0.055)	0.447*** (0.028)	0.19** (0.089)	0.365*** (0.043)
Current Cashflows	0.006*** (0.002)	0.0016*** (0.0003)	0.005*** (0.002)	0.0014*** (0.0004)	0.005** (0.0019)	0.0013*** (0.0003)	0.005*** (0.0019)	0.0015*** (0.0004)
Lagged Cashflows	0.005*** (0.002)	0.0046*** (0.0003)	0.003* (0.0017)	0.004*** (0.0003)	0.004** (0.0017)	0.004*** (0.0003)	0.003* (0.0017)	0.037*** (0.0003)
N observations	11643	11643	11643	11643	11643	11643	11643	11643
N companies	3323	3323	3323	3323	3323	3323	3323	3323
Weighted	No	Yes	No	Yes	No	Yes	No	Yes
Year Dummies	No	No	Yes	Yes	No	No	Yes	Yes

All regressions include firm-fixed effects