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GROWTH, SLOWDOWNS, AND RECOVERIES

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ABSTRACT

We construct and estimate a model that features endogenous growth and technology adoption to study the link between business cycle fluctuations and long-term growth since WWII. The presence of spillover effects from research and development (R&D) imply an endogenous relation between productivity growth and the state of the economy. During the Great Recession, the endogenous component of TFP dropped precipitously, while R&D and long-term growth were not equally affected. The opposite occurred during the 2001 recession, which corresponded to a large decline in R&D. We interpret these results in light of the different forms of financing for investment in physical capital versus R&D. Monetary and fiscal interventions mitigated the drop in real activity and adoption of existing technologies. During the Great Inflation, transitory inflationary shocks led to a persistent productivity slowdown. The growth mechanism induces positive comovement between consumption and investment. Shocks to the marginal efficiency of investment explain the bulk of the low-frequency variation in growth rates.

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1 Introduction

Macroeconomic growth rates exhibit low-frequency patterns often associated with innovation and technological change. The advent of electricity and the introduction of computers are each associated with persistent waves in the trend component of productivity.[1] The adoption and diffusion rate of new technologies is also important for explaining productivity dynamics and for reconciling cross-country differences in economic growth.[2] Despite these efforts in the growth literature, there is no consensus on the macroeconomic sources of prolonged productivity slowdowns and the subsequent recoveries. In particular, there is substantial disagreement in projecting the long-run effects of the recent Great Recession on economic growth (Summers (2013)).[3]

In this paper, we quantitatively examine the driving forces of economic growth at both medium- and long-term frequencies by building and estimating a Dynamic Stochastic General Equilibrium (DSGE) model that incorporates endogenous technological progress and adoption rates. We then use our estimated model to enhance our understanding of two key events in US economic history that presented a persistent productivity slowdown, the Great Recession and the Great Inflation. The model embeds an endogenous growth framework of vertical innovations (Aghion and Howitt (1992), Grossman and Helpman (1991), and Peretto (1999)) and technology adoption (Parente and Prescott (1994)) in a medium-size DSGE framework (Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano and Primiceri (2008)) that features a rich set of macroeconomic shocks. The spillover effects from knowledge accumulation and variation in endogenous technology provide two important transmission channels for business cycle shocks to long-term growth. In equilibrium, total factor productivity (TFP) growth is endogenous and related to research and development (R&D) and technology adoption rates. Thus, this framework allows us to analyze the impact of business cycle disturbances on TFP and trend growth.

Our model produces a link between TFP and the state of the economy through the

[1]See, for example, Jovanovic and Rousseau (2005) and Gordon (2010) for surveys.

[2]Prominent examples include Barro (1991), Parente and Prescott (1994), Barro and Sala-i-Martin (1997), Basu and Weil (1998), Comin and Hobijn (2004), and Comin and Hobijn (2010b)

[3]Benigno and Fornaro (2015), Gordon (2014), and Fernald (2014) are examples that provide opposing views.

endogenous component of TFP. This endogenous component is the result of a process of accumulation, adoption, and utilization of knowledge. The stock of knowledge is accumulated through R&D investment, then knowledge is adopted in order to be in a usable form for production, and finally, resources are expended for the stock of adopted knowledge to be utilized in production. In the estimated model, the endogenous component of TFP explains most of the variability in TFP growth, while the accumulation of knowledge is primarily related to long-run trends in TFP growth. The return on adopting existing technology varies significantly in response to changes in market conditions. Due to high R&D adjustment costs, transitory disturbances are mostly absorbed by endogenous TFP. In other words, the optimal response to variations in the marginal return of technology mostly consists of adjusting the adoption and utilization rates of existing technology, as opposed to changing R&D expenditures. We find this result appealing as the accumulation of knowledge through R&D is a process that requires expending a steady amount of resources, while the decision of how much technology to incorporate in the production process of goods can be more easily adjusted in response to market conditions.

Our estimates suggest that a significant fraction of the medium- and low-frequency variation in growth rates, such as output, consumption, and investment, is attributed to shocks to the marginal efficiency of physical investment (MEI shocks). At the same time, shocks to the marginal efficiency of investment also explain the bulk of the variation at business cycle frequencies of investment growth, consistent with evidence from Justiniano, Primiceri, and Tambalotti (2010, 2011). Therefore, our results suggest a tight link between business cycle fluctuations and long-term growth dynamics. In the model, a positive shock to the marginal efficiency of investment increases investment in physical capital, which raises the marginal productivity of R&D capital (i.e., knowledge capital) due to complementarities in production. Greater accumulation of R&D capital and higher technology adoption and utilization rates lead to a persistent increase in growth due to knowledge spillovers.

Accounting for these two margins of technology adjustment, R&D and adoption and utilization rates, has important implications for the consequences of a recession, especially over longer horizons. We find that the Great Recession was associated with a large drop in technology adoption and utilization rates, while R&D was not significantly affected. In contrast, during the 2001 recession there was a significant decline in R&D investment after the bust of the information technology (IT) bubble, but only a modest change in the adoption rate of existing technology. Consequently, while the current recession has been substantially more severe in the short-term, our model suggests that trend growth was less affected during the Great Recession compared to the 2001 recession, which accords with the empirical evidence from Fernald (2014). While the current model projections suggest that long-run growth prospects have remained relatively stable during the current recession, our results also imply that if market conditions did not improve, R&D would eventually start declining.

Further, counterfactual experiments suggest that during the Great Recession, accommodative monetary and fiscal policies helped to stabilize both R&D rates and the adoption of existing technology, which has important consequences on the trend component of productivity. In a model with exogenous growth, TFP and trend growth do not depend on policymakers' actions. As a result, these models generally imply a steady and relatively fast return to the trend, independent from the actions undertaken by the fiscal and monetary authorities. Instead, in the present model sustaining demand during a severe recession can deeply affect the medium- and long-term outcomes for the economy. This result has important implications for the role of policy intervention during recessions. For example, we believe that the link between policy interventions and growth is important in light of the recent debate on the consequences of performing fiscal consolidations during recessions (Alesina and Ardagna (2010) and Guajardo, Leigh, and Pescatori (2014) provide opposing views).

The differences between the two recessions detected by our estimates are in line with a heuristic interpretation of the two events. The 2001 recession coincided with the end of the IT bubble, an event that particularly affected R&D intensive firms. Our model captures this fact through a shock to the marginal efficiency of R&D (MER), which we find is strongly related with the internal cash flow and the supply of external equity finance for R&D intensive firms, the main sources of financing for R&D. Since R&D projects are often characterized by a high degree of asymmetric information and low asset tangibility, debt financing is more limited (e.g., Brown, Fazzari, and Petersen (2009)). The large negative MER shock preceding the 2001 recession led to persistent decline in R&D, which implies a long-lasting adverse effect on trend growth. In contrast, the 2008 recession originated, or at least coincided, with a severe financial crisis. Shocks to the marginal efficiency of investment can be regarded as a reduced-form way to capture the ease to which firms can access external debt financing. For example, Justiniano, Primiceri, and Tambalotti (2011) show that this shock is highly correlated with the credit spread between the returns on high-yield and AAA corporate bonds. This shock had a sharp, but short-lived impact on R&D, and therefore had less of an impact on trend growth compared to the 2001 recession.

The model has also interesting implications for the interpretation of the Great Inflation of the 1970s. Short-lived inflationary shocks have persistent negative effects on economic growth, primarily through the technology adoption channel. In the estimated model, the oil shock episodes of the 1970s contributed to a decline in the endogenous component of TFP, which led to an extended slump in productivity growth. In the model, a fall in productivity increases real marginal costs, which implies an increase in inflation. At the same time, the positive markup shock reduces demand for factor inputs, including R&D capital. As there are high costs for adjusting R&D, technology adoption and utilization rates fall aggressively while R&D only declines slightly, albeit more persistently. In sum, TFP growth drops sharply and persistently, while the increase in inflation is relatively short-lived.

The endogenous growth mechanism generates positive responses in consumption and investment to investment shocks, which is sometimes a challenge in DSGE models (e.g., Barro and King (1984)). In standard DSGE models, positive investment shocks often lead to a decline (or an initial decline) in consumption, while investment, hours, and output increase. In our model, the investment shocks are amplified, as they affect TFP growth through the knowledge accumulation and endogenous TFP channels. Thus, a positive investment shock increases output more than in the standard models without the endogenous technology margins, which helps our model generate a positive consumption response. Finally, monetary policy shocks induce positive comovement between measured productivity and inflation, consistent with evidence from Evans and dos Santos (2002).

Our approach of estimating a structural model helps to elucidate the link between R&D, growth, and business cycle dynamics. Due to data limitations, measuring the sources of low-frequency growth fluctuations at long horizons is inherently difficult. For example, it would be hard to learn about the impact of R&D by only looking at its effect on growth *decades* later. Instead, our endogenous growth framework imposes joint economic restrictions on the evolution of macroeconomic quantities at short- and long-horizons. Therefore, conditional on the model, the dynamics at business cycle frequencies are also informative about the low-frequency behavior of the economy. This is because, given a parametric specification, the deep parameters that govern high- and low-frequency movements are invariant and can be inferred by examining fluctuations at all frequencies.

This paper is related to the literature linking business cycles to growth.[4] Barlevy (2004) shows that the welfare costs of business cycle fluctuations are higher in an endogenous growth framework due to the adverse effects of uncertainty on trend growth. Aguiar and Gopinath (2007) find that shocks to trend growth are the primary source of fluctuations in emerging markets. Kung and Schmid (2014) examine the asset pricing implications of a stochastic endogenous growth model and relate the R&D-driven low-frequency cycles in growth to long-run risks. Kung (2014) builds a New Keynesian model of endogenous growth and shows how the model can rationalize key term structure facts. In the context of the asset pricing literature on long-run risks based on the work by Bansal and Yaron (2004), our results imply that MEI shocks, typically associated with business cycle fluctuations, are an important source of low-frequency movements in consumption growth. Guerron-Quintana and Jinnai (2013) use a stochastic endogenous growth model to analyze the effect of liquidity shocks on trend growth. Our paper distinguishes itself, as it represents, to the best of our knowledge, the first attempt to estimate a state-of-the-art medium-size DSGE model with endogenous growth. Further, our estimation framework allows us to more precisely identify the macroeconomic sources of low-frequency growth fluctuations.

We also relate to papers examining the causes and long-term impact of the Great Recession. Benigno and Fornaro (2015) analyzes how animal spirits can generate a long-lasting liquidity trap in a New Keynesian growth model with multiple equilibria. Eggertsson and Mehrotra (2014) illustrate how a debt deleveraging shock can induce a persistent, or even permanent, economic slowdown in a New Keynesian model with overlapping generations. Christiano, Eichenbaum, and Trabandt (2014) show how interactions of financial frictions

[4] Also, see Comin (2009) for a general survey of this approach.

with a zero lower bound constraint on nominal interest rates in a DSGE framework can help explain the dynamics of macroeconomic aggregates during the Great Recession. Bianchi and Melosi (2014) link the outcomes of the current recession to policy uncertainty. Our paper focuses on the effects of the Great Recession through the R&D and technology adoption margins, and thus, we view our contribution as complementary to the existing literature.

This paper makes two methodological contributions with respect to the existing literature. We introduce a Schumpeterian growth framework in a medium-size DSGE model with nominal rigidities, captured by Calvo pricing.[5] Second, we structurally estimate the model using Bayesian methods. To the best of our knowledge, this is the first paper that estimates a quantitative model of the business cycle augmented with endogenous growth and technology adoption margins by using data on the amount of R&D investment. In this respect, our work is related to, but differs from the seminal contribution of Comin and Gertler (2006) and the subsequent work by Anzoategui, Comin, Gertler, and Martinez (2016) across several dimensions. First, these papers use an endogenous growth framework with horizontal innovations (i.e., expanding variety model of Romer (1990)) whereas we use a growth model with vertical innovations. Second, we have different interpretations of the 2001 and 2008 recessions compared to Anzoategui, Comin, Gertler, and Martinez (2016). Third, we use our model to study both the Great Inflation and the Great Recession. Finally, we make use of the recently released series for quarterly R&D investment to inform us on the process of knowledge accumulation.

Finally, our paper also relates to models that feature technology adoption. Parente and Prescott (1994), Basu and Weil (1998), Comin and Hobijn (2010a), and Comin, Gertler, and Santacreu (2009). Our model complements these contributions by showing that medium-term fluctuations in technology adoption and utilization rates are mostly driven by shocks to the marginal efficiency of investment. Further, we show that accounting for the technology adoption channel is important for explaining the dynamics of TFP during major economic events, such as the Great Recession and the Great inflation. The connection between market conditions, demand shocks, and measured TFP relates to Bai, Rios-Rull, and Storesletten (2012). Finally, our paper is connected to McGrattan and Prescott (2010), who study the

[5]For a survey on Schumpeterian growth models, see Aghion, Akcigit, and Howitt (2013).

role of intangible investment for explaining the economic boom of the 1990s, and Cao and LHuillier (2014), who explore the role of learning for medium-term fluctuations.

The paper is organized as follows. Section 2 illustrates the model. Section 3 presents the estimates. Section 4 studies the Great Recession and the Great Inflation in light of our model. Section 5 concludes.

2 Model

The benchmark model is a medium-scale DSGE model with endogenous growth and technology adoption. The endogenous growth production setting with vertical innovations follows Kung (2014) and the additional frictions and shocks are standard in the literature and taken from Christiano, Eichenbaum, and Evans (2005).

2.1 Representative Household

There are a continuum of households, each with a specialized type of labor $j \in [0,1]$. Household j is also assumed to have external habits over consumption C_t.

$$E_t \sum_{s=0}^{\infty} \beta^s \zeta_{C,t+s} \left\{ \log(C_{t+s} - \Phi_c \overline{C}_{t+s-1}) - \chi_{t+s} \frac{L_{j,t+s}^{1+\sigma_L}}{1+\sigma_L} \right\},$$

where β is the discount rate, Φ_c is an external habit parameter, C_t denotes consumption, $\overline{C}_t$ is average consumption, L_t denotes the labor service supplied by the household, and σ_L is the inverse of the the Frisch labor supply elasticity. The variable $\zeta_{C,t}$ represents an intertemporal preference shock with mean one and the time series representation:

$$\log(\zeta_{C,t}) = \rho_{\zeta_C} \log(\zeta_{C,t-1}) + \sigma_{\zeta_C} \epsilon_{\zeta_C,t},$$

where $\epsilon_{\zeta_C,t} \sim N(0,1)$. The variable χ_t represents shocks to the marginal utility of leisure and has the following time series representation:

$$\log(\chi_t) = (1-\rho_\chi)\log(\chi) + \rho_\chi \log(\chi_{t-1}) + \epsilon_{\chi,t}.$$

Households are a monopolistic supplier of labor to intermediate firms following Erceg, Henderson, and Levin (2000). In particular, intermediate goods firms use a composite labor input:

$$L_t = \left[\int_0^1 L_{j,t}^{\frac{1}{1+\lambda_w}} dj\right]^{1+\lambda_w}.$$

Employment agencies purchase labor from the households, package the labor inputs, and sell it to the intermediate goods firms. The first-order condition from profit maximization yields the following demand schedule:

$$L_{j,t} = \left(\frac{W_{j,t}}{W_t}\right)^{-\frac{1+\lambda_w}{\lambda_w}} L_t,$$

where $W_{j,t}$ is the wage rate paid to the supplier of $L_{j,t}$. The aggregate wage index paid by the intermediate firms for the packaged labor input L_t is given by the following rule:

$$W_t = \left[\int_0^1 W_{j,t}^{-\frac{1}{\lambda_w}} dj\right]^{-\lambda_w}.$$

The household sets wages subject to nominal rigidities. In particular, a fraction $1-\zeta_w$ can readjust wages. The remaining households that cannot readjust wages will set them according to the following indexation rule:

$$W_{j,t} = W_{j,t-1}\left(\Pi_{t-1}M_{n,t-1}\right)^{\iota_w}\left(\Pi \cdot M_n\right)^{1-\iota_w}.$$

Households own the physical and R&D capital (i.e., knowledge) stocks.[6] Households accumulate the physical stock, $\overline{K}_t$, and rent out physical capital services, K_t, to a competitive capital market at the rate, $P_t r_t^k$, by selecting the physical capital utilization rate u_t^k: $K_t = u_t^k \overline{K}_{t-1}$. Increased utilization requires increased maintenance costs in terms of investment goods per unit of physical capital measured by the function $a_k(u^k)$. In the linearized solution of the model, only the ratio $a_k''\left(u^k\right)/a_k'\left(u^k\right) = \sigma_k$ is relevant for the law of motion of the

[6] We assume the household accumulates both physical and knowledge capital to stay as close as possible to standard medium-size DSGE models, such as Christiano, Eichenbaum, and Evans (2005). The dynamics of the model are quantitatively similar if instead firms accumulated the capital stocks (see, for example, Kung (2014)).

economy, where u^k is the steady-state value for u_t^k.

The household accumulates physical capital subject to the following law of motion:

$$\overline{K}_t = (1-\delta_k)\overline{K}_{t-1} + \left[1 - \Psi_k\left(\zeta_{I,t}\frac{I_t}{I_{t-1}}\right)\right] I_t,$$

where the function Ψ_k is convex and in the steady-state $\Psi_k = 0 = \Psi_k'$. The variable $\zeta_{I,t}$ represents a mean one shock to the marginal efficiency of investment, and evolves as:

$$\log(\zeta_{I,t}) = \rho_{\zeta_I}\log(\zeta_{I,t-1}) + \sigma_{\zeta_I}\epsilon_{\zeta_I,t},$$

where $\epsilon_{\zeta_I,t} \sim N(0,1)$.

Households accumulate knowledge capital $\overline{N}_t$, adopt knowledge capital $\widetilde{N}_t$, and rent adopted knowledge capital services, N_t, to a competitive capital market at the rate $P_t r_t^n$, by selecting the adopted knowledge capital utilization rate u_t^n: $N_t = u_t^n \widetilde{N}_{t-1}$. Increased utilization requires increased costs in terms of investment in R&D capital measured by the function $a_n(u^n)$. In the linearized solution of the model, only the ratio $a_n''(u^n)/a_n'(u^n) = \sigma_n$ is relevant for the law of motion of the economy, where u^n is the steady-state value for u_t^n.

Households accumulate knowledge capital by investing in R&D expenditures, S_t, according to the following law of motion:

$$\overline{N}_t = (1-\delta_n)\overline{N}_{t-1} + \left[1 - \Psi_n\left(\zeta_{S,t}\frac{S_t}{S_{t-1}}\right)\right] S_t,$$

where the function Ψ_n is convex and in the steady-state $\Psi_n = 0 = \Psi_n'$. The variable $\zeta_{S,t}$ represents a mean one shock to the marginal efficiency of R&D investment and evolves as:

$$\log(\zeta_{S,t}) \quad = \quad \rho_{\zeta_S}\log(\zeta_{S,t-1}) + \sigma_{\zeta_S}\epsilon_{\zeta_S,t},$$

where $\epsilon_{\zeta_S,t} \sim N(0,1)$. The shock $\zeta_{S,t}$ can be interpreted as capturing variations in the efficiency with which R&D investment can transformed into new knowledge (e.g., blueprint ideas). Such variations are likely to depend on disturbances that are specific to sectors that are characterized by high R&D intensity.

Technology also needs to be adopted in order to be usable for firms. The households own the stock of adopted knowledge and need to spend J_t in the following law of motion:

$$\widetilde{N}_t = \xi_t H\left(\frac{J_t}{\widetilde{N}_{t-1}}\right)(\overline{N}_{t-1} - \widetilde{N}_{t-1}) + \phi_1 \widetilde{N}_{t-1},$$

where adoption technology $H(\cdot)$ is concave and in the steady state, $H = 1$ and $H' = \frac{1}{\xi(\overline{n}-1)}$. Compared to the existing literature, we model both the process of *adopting* and *utilizing* new technology. In the context of our model, adoption captures the process of transforming new ideas or technology in usable form for production, whereas utilization captures the costs associated with directly implementing the new technology in the production process. We find that accounting for these two technological margins is important when confronting the model with the data, because the adoption margin is more important for explaining low-frequency phenomena, while the utilization margin acts mostly at high frequencies.

The budget constraint for the household is:

$$\begin{aligned} P_t C_t + P_t \zeta_{\Upsilon,t}^{-1} I_t + P_t S_t + B_t &= B_{t-1}R_{t-1} + P_t \overline{K}_{t-1}[r_t^k u_t^k - a_k(u_t^k)] + \\ &\quad P_t \widetilde{N}_{t-1}[r_t^n u_t^n - a_n(u_t^n)] + W_t L_t - T_t P_t - P_t J_t, \end{aligned}$$

where $\zeta_{\Upsilon,t}^{-1}$ captures the cost, in terms of consumption goods, of one unit of investment. Since the currency price of the consumption good is P_t, the currency price of a unit of investment good is $P_t \zeta_{\Upsilon,t}^{-1}$. The law of motion for $\zeta_{\Upsilon,t}^{-1}$ is given by:

$$\log(\zeta_{\Upsilon,t}) = \rho_{\zeta_\Upsilon} \log(\zeta_{\Upsilon,t-1}) + \sigma_{\zeta_\Upsilon} \epsilon_{\zeta_\Upsilon,t},$$

where $\epsilon_{\zeta_\Upsilon,t} \sim N(0,1)$. We allow for changes in the relative price of physical investment to capture technological progress that affects the rate of transformation between consumption and investment, but that is not directly linked to the accumulation of knowledge through R&D investment. Variation in the relative price of investment is needed mostly to correctly capture the process of physical capital accumulation that occurred in the US starting from World War II. Furthermore, these relative price shocks allow us to interpret the shocks to the marginal efficiency of physical investment in a way that is in line with the literature.

2.2 Firms

A representative firm produces the final (consumption) goods in a perfectly competitive market. The firm uses a continuum of differentiated intermediate goods, $Y_{j,t}$, as input in the CES production technology:

$$Y_t = \left(\int_0^1 Y_{j,t}^{1/\lambda_{f,t}} \, dj \right)^{\lambda_{f,t}},$$

where $\lambda_{f,t}$ is the markup over marginal cost for intermediate goods firms. The law of motion for $\lambda_{f,t}$ is given by:

$$\log(\lambda_{f,t}) = \left(1 - \rho_{\lambda_f}\right) \log(\lambda_f) + \rho_{\lambda_f} \log(\lambda_{f,t-1}) + \sigma_{\lambda_f} \epsilon_{\lambda_{f,t}}.$$

The profit maximization problem of the firm yields the following isoelastic demand schedule:

$$Y_{j,t} = Y_t \left(\frac{\mathcal{P}_{j,t}}{\mathcal{P}_t} \right)^{-\lambda_{f,t}/(\lambda_{f,t}-1)},$$

where $\mathcal{P}_t$ is the nominal price of the final goods and $\mathcal{P}_{j,t}$ is the nominal price of intermediate good i. The price of final goods is obtained integrating over the intermediate goods prices. The intermediate good j is produced by a price-setting monopolist using the following production function:

$$Y_{j,t} = \max\left\{ K_{j,t}^{\alpha} \left(A_t N_{j,t}^{\eta} N_t^{1-\eta} L_{j,t} \right)^{1-\alpha} - F \cdot \widetilde{N}_t, 0 \right\},$$

where $N_t \equiv \int_0^1 N_j dj$ is public knowledge and the parameter $\eta \in [0,1]$. In addition, the inputs $K_{j,t}$ and $N_{j,t}$ are accumulated using the final goods. The variable A_t represents a stationary aggregate productivity shock that is common across firms and evolves in logs as an AR(1) process:

$$a_t = (1-\rho)a^{\star} + \rho a_{t-1} + \sigma \epsilon_t,$$

where $a_t \equiv \log(A_t)$, $\epsilon_t \sim N(0,1)$ is i.i.d., and $a^{\star} > 0$ is the unconditional mean of a_t. Following Calvo (1983), a fraction $1 - \zeta_p$, randomly chosen, of the intermediate goods firms are permitted to reoptimize their price every period. Of the remaining firms, a (randomly selected) fraction $1 - \iota_p$ must set $P_{it} = \Pi P_{i,t-1}$ and a fraction ι_p sets $P_{i,t} = \Pi_{t-1} P_{i,t-1}$, where

$\Pi_t = P_t/P_{t-1}$ is gross inflation.

2.3 Market Clearing and Fiscal Authority

The market clearing condition for this economy is $C_t + \zeta_{\Upsilon,t}^{-1} I_t + S_t + G_t = Y_t^G$, where G_t denotes government expenditures and Y_t^G is measured GDP (i.e., $Y_t^G = Y_t - a_k(u_t^k)\overline{K}_{t-1} - a_n(u_t^n)\widetilde{N}_{t-1} - J_t$). The government issues short-term bonds and moves lump-sum taxes T_t in order to finance government expenditure. Government expenditure follows an exogenous law of motion:

$$\hat{g}_t = \rho_g \hat{g}_{t-1} + \sigma_g \epsilon_{g,t},$$

where $\epsilon_{g,t} \sim N(0,1)$, $\hat{g}_t = \ln(g_t/g)$, and $g_t \equiv G_t/\widetilde{N}_t$. In the steady-state, $G/Y^G = \eta_G$.

The central bank follows a modified Taylor (1993) rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} \left(\frac{\Delta Y_t}{\Delta Y}\right)^{\phi_{\Delta y}}\right]^{1-\rho_R} e^{\sigma_R \epsilon_{R,t}}$$

2.4 Solving the Model

The trend component in TFP, $\widetilde{N}_t$, is endogenous. In order to induce stationarity, aggregate variables, such as, consumption, R&D, investment, output and government expenditures, are normalized by $\widetilde{N}_t$. Once the model is rewritten in terms of stationary variables, the nonstochastic steady state can be computed, which includes the endogenous trend growth rate, $\Delta\widetilde{N}$. In particular, the trend growth rate is a function of the deep parameters of the model:

$$\Delta\widetilde{N} = \beta\left(1 - \delta_n + \xi\right).$$

After obtaining the non-stochastic steady state values, we log-linearly approximate the equations around the steady-state values (the linearized equations are in the appendix).

2.5 TFP Growth

Imposing the symmetric equilibrium conditions, the aggregate variable output $\widetilde{Y}_t$ can be expressed as:

$$\widetilde{Y}_t = (Z_t L_t)^{1-\alpha} K_t^{\alpha},$$

where measured TFP, Z_t, is endogenous and depends on the utilization rate of adopted knowledge:

$$Z_t = A_t u_t^n \widetilde{N}_{t-1}.$$

As in Comin and Gertler (2006) and Kung and Schmid (2014), the trend component in TFP, $\widetilde{N}_{t-1}$, is endogenous and time-varying. For the discussion of the results below, we define $a_t \equiv \log(A_t)$ as the *exogenous* stationary shock to TFP, u_t^n is the technology utilization rate, $\overline{N}_{t-1}$ is the stock of knowledge, $\widetilde{N}_{t-1}$ is the stock of adopted knowledge, and $N_t \equiv u_t^n \widetilde{N}_t$ is the endogenous component of TFP.

3 Estimates

This section presents the main estimation results. We estimate the model using a Metropolis Hastings algorithm. As observables, we use seven series of U.S. quarterly data: real GDP per capita, annualized quarterly inflation, the federal funds rate (FFR), real consumption per capita, investment in physical capital in terms of consumption units, investment in R&D (knowledge) capital in terms of consumption units, and the relative price of investment. All variables except for inflation and the FFR enter as log differences and are downloaded by the BEA website. The sample spans 1954:Q3 to 2013:Q3. To the best of our knowledge, this is the first paper that makes use of the newly released series for quarterly R&D in a structural estimation.

3.1 Parameter Estimates

Table 1 reports priors, modes, means, and 90% error bands for the DSGE parameters. The priors are diffuse and in line with the literature. For the parameters that characterize the endogenous growth mechanism, we choose diffuse priors and take an agnostic view on their likely values, given that there is no previous evidence to guide us. We also specify a prior on the steady-state trend growth rate: $100\Delta\widetilde{N} \sim N(.45, .05)$. Given that steady state growth in the model is a function of several model parameters, this choice translates in a joint prior on these model parameters.

The posterior parameter estimates suggest a significant degree of price stickiness and habit formation consistent with the literature (e.g., Altig, Christiano, Eichenbaum, and Linde (2011) and Del Negro, Schorfheide, Smets, and Wouters (2007)). We find very high adjustment costs for R&D, S''_N, and a small elasticity of firm-specific R&D with respect to its output, η, which both make R&D less responsive to macroeconomic shocks and is important for capturing persistent R&D dynamics. Similarly, the parameters associated with the adjustment and depreciation rate of the adoption process (H'' and ϕ_1, respectively) imply that adoption varies mostly at low frequencies, as we will show in the next subsection. On the other hand, the low value for σ_n implies that the technology utilization rate is very responsive to changes in the return of adopted knowledge. We interpret these two findings as implying that R&D and adoption needs to be carried on consistently over time in order to produce significant results and that the important margin for technology adjustment in the short-run relies on varying the utilization rate of adopted knowledge. Furthermore, the small value for η also implies that there are large positive spillover effects from innovation, which is consistent with microeconomic evidence from Griliches (1992). The depreciation rate for R&D capital turns out to be substantially lower than the one for physical capital, which again is a reflection of the smooth R&D dynamics.

3.2 Variance decomposition

In this section, we analyze the properties of the estimated model in the frequency domain. This analysis will prove useful to understand our interpretation of the 2001 and 2008 recessions. Before proceeding, it is worth recalling that the model implied TFP consists of three different components: The *stationary technology shock*, the *technology utilization rate*, and *adopted knowledge*. Namely:

$$TFP_t = \underset{\text{Tech. Shock}}{A_t} * \underset{\text{Utilization}}{u_t^n} * \underset{\text{Ad. Knowledge}}{\widetilde{N}_{t-1}}.$$

The product of utilization and adopted knowledge is the *endogenous component of TFP*, $N_t = u_t^n \widetilde{N}_{t-1}$, which includes the endogenous trend component. The stationary technology shock, A_t, is the *exogenous component of TFP*. As we will see, the endogenous component of TFP captures the bulk of the fluctuations in the model implied TFP, while the long-term component, adopted knowledge, is fairly stable. These definitions imply that TFP growth and the endogenous component of TFP can be expressed as:

$$\begin{aligned} \Delta tfp_t &= \underset{\Delta\text{Exogenous}}{\Delta a_t} + \underset{\Delta\text{Endogenous}}{\Delta n_t} \\ \Delta n_t &= \underset{\Delta\text{Utilization}}{\Delta u_t^n} + \underset{\Delta\text{Ad. Knowledge}}{\Delta \widetilde{n}_{t-1}}, \end{aligned}$$

where we have used lower case letters to denote the logs of the corresponding economic variables.

Table 2 decomposes the model-implied variance of the observed variables and the components of the model-implied TFP across three frequency intervals. Long-term frequencies correspond to cycles of more than 50 years, medium-term frequencies are associated with cycles between 8 and 50 years, whereas business cycle frequencies correspond to cycles of a duration between 0.5 and 8 years. For all the observed variables the volatility at medium-term frequencies plays a significant role, consistent with the findings from Comin and Gertler (2006). In fact, for the FFR, labor hours, and R&D growth more than 50% of volatility is explained by medium-term fluctuations. Furthermore, for consumption growth, investment growth, and GDP growth, the variance of the medium-term and business cycle components are quite similar in magnitude.

For model-implied TFP, the decomposition across frequencies varies depending on its components, endogenous TFP ($N_t = u_t^n \widetilde{N}_{t-1}$) and adopted knowledge ($\widetilde{N}_t$). The growth rate of TFP and endogenous TFP exhibit fluctuations mostly at business cycle frequencies, which reflects the sizable estimated value of the elasticity of technology utilization with respect to its return. On the other hand, the fluctuations of the growth rate of adopted knowledge are mostly at low frequencies and, to some extent, at medium cycle frequencies, which is due to both the high R&D adjustment costs and the persistence in the technology adoption process.

We also find that most of the variation in the model implied TFP is attributed to the fluctuations in the endogenous TFP component (more than 60%) and that this fraction is larger at lower frequencies. Figure 1 provides a visual characterization of this result by plotting the evolution of the model-implied TFP growth (dashed black line), along with the endogenous component of TFP (solid blue line), and adopted knowledge component of TFP growth (red dotted line). These series are obtained extracting the corresponding smoothed series based on the posterior mode estimates. Consistent with variance decomposition above, TFP growth appears substantially more volatile with respect to the growth rate of knowledge itself. In principle, such large fluctuations could be explained by changes in the exogenous component of TFP. However, it is evident that changes in the endogenous component of TFP capture the bulk of the fluctuations in TFP growth, as the endogenous component tracks quite closely the medium-term fluctuations in TFP, whereas the exogenous fluctuations seem to be mostly important at high frequencies. In other words, this figure corroborates the finding that the most important margin for explaining TFP growth dynamics consists of changes in endogenous TFP, as opposed to fluctuations in the accumulation of knowledge through R&D or exogenous fluctuations in technology captured by the stationary technology shock.

It is then interesting to understand what forces drive the observed fluctuations. In order to address this question, Table 3 reports the variance decomposition with respect to the structural shocks that affect the macroeconomy. The top panel refers to the variance decomposition at business cycle frequencies, while the lower panel refers to medium-term cycle frequencies.

The first observation that is worth emphasizing is that shocks to the marginal efficiency of investment play a central role for *all* of the observed variables included in our estimates, especially at medium-term frequencies. At these frequencies, the marginal efficiency of investment explains over 40% of the variance for most of the endogenous variables, with a peak of 82% for the FFR. Furthermore, the marginal efficiency of investment plays a key role at business cycle frequencies for investment growth and, consequently, for GDP growth.

The dynamics of the endogenous components of TFP growth differ quite substantially from each other. For the adopted knowledge growth component, shocks to the marginal efficiency of R&D play a key role. This is due to fact that knowledge growth is very persistent and the MER shocks are particularly important for low-frequency fluctuations. In contrast, for the endogenous component of TFP, the price markup shock explains over 40% of the overall volatility, while MEI and stationary technology shocks both explain around 20%. Overall, these results suggest that markup shocks can have important effects at business cycle frequencies while low-frequency movements in growth are mostly driven by MEI and MER shocks.

In fact, markup shocks explain a sizeable fraction of consumption fluctuations at business cycle frequencies (around 16%). Preference shocks also explain a sizeable fraction of consumption volatility at business cycle frequencies, but they are mostly irrelevant for medium-term fluctuations. As a result, preference shocks play a modest role for explaining the bulk of the overall consumption volatility. In addition, the markup shock explains most of the business cycle variation in wage growth (around 80%) and inflation (around 45%). The fact that markup shocks explain the bulk of the business cycle dynamics of inflation, and at the same time have large effects on the growth rate of endogenous TFP, creates an interesting link between inflationary shocks and growth that we will explore in Subsection 4.2.

Overall, we provide new evidence supporting the importance of shocks to the marginal efficiency of investment for economic fluctuations, particularly at medium and low frequencies. As in Justiniano, Primiceri, and Tambalotti (2010) this shock is important for business cycle fluctuations of investment. However, our estimates suggest that this shock plays a key role to explain medium-term fluctuations of *all* observed variables, and not just GDP and investment. Given that the medium-term frequencies explain a significant fraction of the overall volatility, shocks to marginal efficiency of investment are therefore a driving force for the overall macroeconomic volatility of the observed variables. Our evidence is also consistent with the asset market literature, which shows that investment-specific shocks are an important source of systematic risk and therefore stock market returns (e.g., Papanikolaou

(2011) and Kogan and Papanikolaou (2014)).

We find the transmission of a typical business cycle shock, such as the MEI shock, to medium cycle fluctuations interesting in light of the fact that Justiniano, Primiceri, and Tambalotti (2010) show that the MEI shock capture costs of external debt financing. In our model, knowledge spillovers from R&D accumulation along with technology adoption and utilization rates provide transmission channels of macroeconomic shocks to medium- and long-term growth. More broadly, our estimation suggests a tight link between business cycles and medium-term fluctuations, which supports the findings of Comin and Gertler (2006). The role played by this shock for the lower frequency movements of consumption growth are also interesting in light of the long-run risks literature (e.g., Bansal and Yaron (2004)) that focuses on the comovement between consumption growth and asset returns at longer horizons. We consider this a promising direction for future research. In the next section, we focus on impulse responses to better understand the propagation of the shocks.

3.3 Impulse responses

This section illustrates the key model mechanisms through impulse response functions. Figure 2 displays impulse response functions from a positive shock to the marginal efficiency of physical investment. A positive investment shock triggers more investment in physical capital. Given the complementarity of the factor inputs, a larger physical capital stock increases the marginal productivity of adopted knowledge, which leads to an increase in the adoption and utilization of existing technology along with a smooth increase in R&D. More resources devoted to improving technology raises TFP and also increases trend growth due to the spillover effects from knowledge accumulation. Note that the model also produces positive comovement in consumption and investment, which is sometimes a challenge for standard medium-size DSGE models such as Christiano, Eichenbaum, and Evans (2005). After a positive investment shock, the increase in R&D and endogenous technology amplify the output response by improving both the level and trend components of TFP persistently. Higher current and future levels of output consequently induce a positive consumption response. The positive comovement of macroeconomic quantities to investment shocks allow these shocks to be the main driver of business cycles and low-frequency movements in growth rates.

Figure 3 plots impulse response functions to a positive shock to the marginal efficiency of R&D (MER). A positive MER shock directly induces more R&D investment, and subsequently, increases in adoption and technology utilization. Given the timing lag from the adoption process (to convert knowledge to a usable form for production) and the stickiness in the adjustment of R&D and adoption, the impact on TFP is delayed significantly compared to the response to a MEI shock. Consequently, the impact on other macroeconomic quantities, such as consumption, GDP, hours, and investment exhibit this delayed reaction. In fact, there is an initial dip in investment, as resources in the economy are devoted initially to boosting technology. These key differences in the responses to the MEI and MER shocks are important for capturing salient features of the 2001 and 2008 recessions, which is explored in Section 4.1.

Figure 4 shows impulse response functions from a positive price markup shock.[7] This shock directly increases inflation via the model-implied Phillips curve. Also, a positive markup shock reduces demand for factor inputs, which reduces labor hours, physical and R&D investment. Given high R&D adjustment costs, the R&D response is more gradual than the response of physical investment and labor hours. It is worth emphasizing that while the technology shock is very transitory (see lower left panel), the effects on macroeconomic quantities are quite persistent, and is primarily due to the medium-term dynamics of adopted knowledge. In short, the model generates endogenous persistence in the cycle and trend components of macroeconomic variables.

Figure 5 displays the impulse response functions to a contractionary monetary policy shock. A tightening of monetary policy increases the FFR and lowers the price level. Due to sticky prices, aggregate demand falls and the real rate rises, which discourages investment in physical capital and R&D. The decline in R&D and the endogenous component of TFP leads to a decline in TFP after a contractionary monetary policy shock, consistent with empirical evidence from Evans and dos Santos (2002). Further, the drop in R&D lowers the trend component of TFP due to the endogenous growth channel. Note that response of R&D is

[7]We find that stationary technology shocks have similar effects. This will be useful when accounting for the link between high-frequency movements of inflation and the productivity slowdown during the Great Inflation.

significantly more persistent than the other macroeconomic variables, which is a reflection of the high R&D adjustment costs.

4 Two productivity slowdowns

In this section, we analyze two key events in US economic history that were associated with productivity slowdowns. We first focus on the Great Recession, and then, we investigate the Great Inflation.

4.1 The Great Recession

The most recent recession has generated concerns about the possibility of a prolonged slowdown. Following the speech delivered by Larry Summers (Summers (2013)), some economists have become interested in the possibility of a "secular stagnation" similar to the one that characterized the aftermath of the Great Depression according to Hansen (1939). Eggertsson and Mehrotra (2014) builds a model that can deliver secular stagnation as a result of household deleveraging or a decline in the population growth rate. Gordon (2014) argues that the US might be heading toward a prolonged period of reduced growth. On the other hand, using projections from a calibrated model, Fernald (2014) finds that trend growth remained stable after the Great Recession.

Our model provides a useful framework to address these concerns from a quantitative point of view, given the strong linkages between business cycle fluctuations and long term growth. Figure 6 analyzes the Great Recession through the lens of our model. The solid blue line reports smoothed estimates at the posterior mode for investment, knowledge growth, and the endogenous component of TFP over the past 15 years. The dashed black line describes a counterfactual simulation in which all policy shocks are set to zero since the beginning of the crisis. Specifically, starting from the first quarter of 2008 we set the filtered government expenditure shocks, monetary policy shocks, and inflation target shocks to zero.

The first aspect that emerges from this analysis is that while the recession has implied a significant fall in investment in physical capital, the growth rate for knowledge has been less affected. Instead, the fall in investment has determined a significant and persistent decline in the utilization rate of existing technology due to the decline in the marginal return of adopted technology. As a result, endogenous TFP has fallen significantly (see right panel). Interestingly, this pattern was reversed during the 2001 recession. In the 2001 recession, the economy experienced a relatively small fall of investment in physical capital, a substantial fall in the growth rate of knowledge (after the large accumulation of R&D during the IT boom in the 1990's), and only a relatively modest decline in endogenous TFP. The knowledge growth rate never really recovered, and instead, stabilized at a lower level until the 2008 recession. The decline in the growth rate of knowledge during the 2008 recession is visibly smaller, especially when taking into account that the 2008 recession was much more severe.

A heuristic interpretation of the two events relate to the sources of financing. The 2001 recession coincided with the end of the IT bubble, an event that particularly affected high tech firms (i.e., high R&D intensity firms). Our model captures this fact through a shock to the marginal efficiency of R&D (MER), which we find is strongly related with the internal cash flow and the supply of external equity finance for R&D intensive firms,[8] the main sources of financing for R&D. Since R&D projects are often characterized by a high degree of asymmetric information and low asset tangibility, debt financing is more limited (e.g., Brown, Fazzari, and Petersen (2009)). The large negative MER shock preceding the 2001 recession, illustrated in the right panel of Figure 7, led to a persistent decline in R&D, which implies a long-lasting adverse effect on trend growth. In contrast, the 2008 recession originated from a severe financial crisis. As shown in Justiniano, Primiceri, and Tambalotti (2011), shocks to the marginal efficiency of investment are highly correlated with the credit spread between the returns on high-yield and AAA corporate bonds and can be regarded as a reduced-form way to capture the ease to which firms can access external debt financing. In the left panel of Figure 7, we observe a large negative spike in the MEI series at the onset of the recession in 2008. This shock had a sharp, but short-lived impact on R&D, and therefore had less of an impact on trend growth compared to the 2001 recession.

The top panel of figure 8 plots the R&D series for high tech firms (dash-dot black line), non-high tech firms (dashed blue line), and all firms (solid red line) as a percentage of GDP. Observe that the R&D of the tech firms drive most of the fluctuations in aggregate R&D

[8]The correlation between cash flow and the MER is 0.63 for high tech firms.

dynamics and these firms have steadily increased their share of R&D expenditures relative to non-tech firms since the 1980's. Thus, shocks to the financial constraints of high tech firms have important consequences for aggregate innovation dynamics. The middle panel plots R&D expenditures (dashed blue line), cash flow (solid red line), and new equity share issues (dashed black line) as a percentage of GDP for tech firms, while the bottom panel plots the same series for non-tech firms.[9] From the middle panel, we can see that the persistent decline in R&D for tech firms following the 2001 recession coincides with a sharp decline in cash flow and equity issuance, the main sources of financing for R&D. In contrast, the drop in R&D after the 2008 recession was only short-lived as there was a quick rebound in R&D, and cash flows and equity issues fell significantly less than during the 2001 recession. For non-tech firms, the three series are relatively stable compared to the tech firms, reaffirming the fact that tech firms are the key drivers of innovation over the past three to four decades.

These results have important implications for the long-term consequences of the current recession. On the one hand, it seems that the low-frequency trend component (knowledge growth) has not been substantially affected, implying that long-run growth remained stable. On the other hand, as we have shown in Subsection 3.3, the consequences of a slowdown on the adoption rate of technology can persist for many years, implying that it might take a significant amount of time before the economy closes the gap with respect to the trend component. Furthermore, the 2008 recession has exacerbated a pre-existing downward trend in the growth rate of knowledge that started with the 2001 recession.

In this respect, it is interesting to analyze the role of policymakers' behavior. Modeling unconventional monetary policy or changes in policy rules is beyond the scope of the paper. However, it is still instructive to study the implications of policy shocks. The counterfactual simulation reported in Figure 6 shows that absent policy shocks, the growth rate of knowledge would have been only mildly affected, but the extent of the recovery in investment and adoption of existing technology would have been much more contained.

These results have important implications for the role of policy interventions during recessions. In models with exogenous growth, TFP does not depend on policymakers' actions. As a result, these models generally predict a steady and relatively fast return to the trend,

[9]Tech firms are defined as firms with the following SIC code: 283, 357, 366, 367, 382, 384 or 737.

independent from the actions undertaken by the fiscal and monetary authorities. Instead, in the present model sustaining demand during a severe recession can deeply affect the medium and long term consequences for the economy. Policymakers cannot intervene each period to permanently alter the trend growth rate of the economy.[10] This would violate the notion of the equilibrium steady-state and be subject to the Lucas critique. However, policymakers can substantially reduce the long-term consequences of a recession.

4.2 The Great Inflation

The Great Inflation and the productivity slowdown that occurred in the 1970's have attracted a lot of attention in the literature. Several explanations have been proposed for why inflation rose during the 1960's and 1970's. Orphanides (2002), Primiceri (2006), and Sargent, Williams, and Zha (2006) have focused on central bankers' misperceptions about the state and structure of the economy, Clarida, Gali, and Gertler (2000), Lubik and Schorfheide (2004), and Bianchi (2013) provide support in favor of violations of the Taylor principle, and Cochrane (1998), Sims (2011), and Bianchi and Ilut (2012) emphasize a dysfunctional interaction between the monetary and fiscal authorities.

During the 1970's, movements in inflation exhibited both strong low-frequency and business cycle components. The former has been often explained in light of a persistent productivity slowdown that arguably led to changes in policymakers' behavior. The latter was mostly determined by two oil crises that occurred in 1973/1974 and in 1979. In what follows, we will use our model to highlight the link between these two components.

Figure 9 reports the series for inflation and the model implied growth rate for endogenous TFP based on the parameter values from the posterior mode. The red dashed line corresponds to the actual data, while the solid blue line captures the variation in the variables that is due to the markup and stationary technology shocks. This is obtained by using a counterfactual simulation in which all shocks except the markup and stationary technology shocks are set to zero. It is worth emphasizing that the endogenous component of TFP does

[10]See Barro and Sala-i-Martin (1992) for a model where public finance can affect the steady state growth rate.

not include the stationary technology shock:

$$TFP_t = \underbrace{A_t}_{\text{Tech. Shock}} * \underbrace{u_t^n \widetilde{N}_{t-1}}_{\textit{Endog.}\text{ TFP}}.$$

Therefore, movements in the growth rate of endogenous TFP are not the result of an accounting identity, but derive from the endogenous responses of the technology utilization rate, u_t^n, and the stock of adopted knowledge, $\widetilde{N}_{t-1}$, to a stationary technology shock, A_t. We focus on endogenous TFP, as opposed to $\widetilde{N}_{t-1}$ only, because as shown above, it captures the bulk of TFP fluctuations.

The counterfactual series for inflation tracks inflation dynamics very closely at high frequencies. This is in line with the variance decomposition results that show that stationary technology shocks and markup shocks explain more than 50% of inflation fluctuations at business cycle frequencies. However, the right panel shows that these shocks also have a visible impact on the persistent component of TFP. In other words, the results suggest that a significant fraction of the decline in measured productivity that occurred in the 1970's can be explained in light of *short-lived* inflationary shocks (e.g., oil shocks) because of their impact on the growth rate of adopted knowledge. These results are in line with the evidence presented in Section 3.3: A markup shock (or a stationary technology shock) has an immediate and short-lived impact on inflation, but has a prolonged effect on the adoption and utilization rates of existing technology and a very persistent effect on the accumulation of knowledge itself.

When TFP is endogenous, the consequences of the oil shocks of the 1970's are quite different than in the exogenous TFP setting. While all shocks have an impact on TFP through the knowledge and adoption components, markup and stationary technology shocks are different to the extent that they move growth and inflation in opposite directions. As a result, our model suggests a link between the productivity slowdown, a low-frequency phenomenon, and short-lived inflationary shocks, the oil shocks. While other factors might have contributed to the productivity slowdown, we believe that a model featuring endogenous growth introduces a new dimension for the analysis of the events of the 1970s. This is for two reasons. First, the fact that a short-lived inflationary shock can have persistent consequences on the trend can easily lead to misperceptions about the nature a of a productivity slowdown. This, in turn, might cause policy mistakes. Second, due to the link between the high- and low-frequency fluctuations, policymakers might be tempted to accommodate these shocks in order to mitigate their long-run consequences on growth. In both cases, policymakers' actions could lead to a progressive increase in the low-frequency component of inflation. This would create a link between trend inflation and higher frequency fluctuations.

5 Conclusions

In this paper, we build and estimate a medium-size DSGE model that features endogenous growth and technology adoption. Positive externalities from knowledge accumulation provide a economic channel linking business cycle shocks to long-run growth through the trend component of TFP. The endogenous technology adoption and utilization rates provide a strong propagation channel at medium-term frequencies through the endogenous component of TFP. We find that shocks to the marginal efficiency of physical investment explain a large share of the volatility of all macroeconomic variables, and not just that of investment. This is because these shocks have large effects at medium-term frequencies that, in turn, capture a large fraction of the overall volatility. The endogenous growth margin also helps the model to generate positive comovement in consumption and investment in response to a MEI shock, which is sometimes a challenge for standard DSGE models. More broadly, our model estimation suggests strong linkages between business cycle fluctuations and low-frequency movements in aggregate growth rates.

We then use our estimated model to interpret two major economic events and analyze their long-run consequences. First, we show that while during the Great Recession there was a significant decline in investment and in endogenous TFP, the trend component was not equally affected. In the context of our model, this implies that the most recent recession had severe consequences in the short- and medium-term, but long-run trend growth remained relatively stable. The opposite was true during the 2001 recession, which triggered a persistent decline in the growth rate of knowledge. We interpret the difference between the two recessions in light of the different forms of financing for investment in physical capital and R&D. Second, we show that during the Great Inflation of the 1970's, short-lived inflationary shocks, like oil shocks, contributed to the low-frequency productivity slowdown over the decade due to their persistent effects on adopted knowledge and R&D accumulation. In short, our paper highlights the importance of studying growth and business cycles in a unified setting for understanding macroeconomic dynamics.

Appendix A. System of linearized equations

This appendix reports the linearized system of equations used for the estimation.

1. Firms, "marginal cost" in terms of both factor costs:

$$\begin{aligned}(1+(1-\alpha)\eta)\widehat{mc}_t &= \alpha\widehat{r}^k_t + (1-\alpha)(\widehat{w}_t - \widehat{a}_t) - (1-\alpha)\eta\left(\frac{y}{y+F}\right)\widehat{y}_t \\ &+ \left[(\eta-1)(1-\alpha)\frac{1}{\sigma_n} + \eta(1-\alpha)\right]\widehat{r}^n_t + (\eta-1)(1-\alpha)\widehat{\mu}_{n,t}\end{aligned}$$

2. Firms, marginal cost in terms of rental rate of capital:

$$\widehat{mc}_t = \widehat{r}^k_t - (1-\alpha)\left(\widehat{a}_t + \widehat{u}^n_t + \widehat{L}_t - \widehat{u}^k_t - \widehat{\overline{k}}_{t-1}\right)$$

3. Firms, real rental rate of R&D capital:

$$\widehat{r}^n_t = \widehat{mc}_t + \alpha(u^k_t + \overline{k}_{t-1} - u^n_t) + (1-\alpha)(\widehat{a}_t + \widehat{L}_t)$$

4. Phillips curve:

$$\hat{\pi}_t = \left(\frac{1}{1+\beta\iota_p}\frac{1-\zeta_p}{\zeta_p}\right)\left(\frac{1-\zeta_p\beta}{\tilde{\theta}_1}\right)\widehat{mc}_t + \left(\frac{\iota_p}{1+\beta\iota_p}\right)\widehat{\pi}_{t-1} + \left(\frac{\beta}{1+\beta\iota_p}\right)E_t\widehat{\pi}_{t+1} + \frac{1}{1+\beta\iota_p}\widehat{\lambda}_{f,t}$$

where $\tilde{\theta}_1 = \left(1 - \frac{(1-\alpha)\eta}{1+(1-\alpha)\eta}\frac{\lambda_f}{\lambda_f-1}\frac{y}{y+F}\right)$.

5. Households, consumption:

$$\widehat{\lambda}_{n,t} = -\frac{\Phi_c}{M_n-\Phi_c}\widehat{\mu}_{n,t} - \frac{M_n}{M_n-\Phi_c}\widehat{c}_t + \frac{\Phi_c}{M_n-\Phi_c}\widehat{c}_{t-1}$$

6. Households, labor:

$$\begin{aligned}
\widehat{\tilde{w}}_t &= \frac{(1-\beta\zeta_w)}{1-\delta\sigma_L}\left(\frac{\beta(1-\delta\sigma_L)\zeta_w E_t\left[\widehat{\tilde{w}}_{t+1}+\widehat{w}_{t+1}\right]}{1-\beta\zeta_w}-\widehat{\lambda}_{n,t}+\sigma_L\widehat{L}_t\right. \\
&+ \frac{\beta(1-\delta\sigma_L)\zeta_w\left(E_t\left[\widehat{\mu}_{n,t+1}+\widehat{\pi}_{t+1}\right]-\iota_w\left(\widehat{\mu}_{n,t}+\widehat{\pi}_t\right)\right)}{1-\beta\zeta_w} \\
&- \left.\frac{(1-\delta\sigma_L)\widehat{w}_t}{1-\beta\zeta_w}-\delta\sigma_L\widehat{w}_t\right)
\end{aligned}$$

7. Labor supply index:

$$(1-\zeta_w)\widehat{\tilde{w}}_t = \zeta_w\left(\widehat{w}_t+\widehat{\pi}_t+\widehat{\mu}_{n,t}\right)-\zeta_w\left(\widehat{w}_{t-1}+\iota_w\left(\widehat{\pi}_{t-1}+\widehat{\mu}_{n,t-1}\right)\right)$$

8. Households, bonds:

$$0=\zeta_{C,t}\left(1-\rho_{\zeta_C}\right)+\widehat{\lambda}_{n,t}-E_t\widehat{\lambda}_{n,t+1}-\widehat{R}_t+E_t\widehat{\pi}_{t+1}+E_t\widehat{\mu}_{n,t+1}$$

9. Households, physical capital:

$$0=\zeta_{C,t}\left(1-\rho_{\zeta_C}\right)+\widehat{\lambda}_{n,t}-E_t\widehat{\lambda}_{n,t+1}-E_t\widehat{R}^k_{t+1}+E_t\widehat{\pi}_{t+1}+E_t\widehat{\mu}_{n,t+1}$$

10. Return on physical capital: then

$$\widehat{R}^k_t=\frac{\Pi}{q^kR^k}r^k\widehat{r}^k_t+\frac{\Pi}{R^k}(1-\delta_k)\widehat{q}^k_t+\widehat{\pi}_t-\widehat{q}^k_{t-1}$$

where $q^k=1$.

11. Households, investment in physical capital:

$$\begin{aligned}0 &= \widehat{q}_t^k + \widehat{\zeta}_{\Upsilon,t} - \Psi_k'' M_n^2 (1+\beta)\,\widehat{i}_t + \widehat{\zeta}_{I,t} - \Psi_k'' M_n^2 \hat{\mu}_{n,t} \\ &+ \Psi_k'' M_n^2 \widehat{i}_{t-1} + \beta M_n^2 \Psi_k'' E_t\left[\widehat{i}_{t+1}\right] + \beta M_n^2 \Psi_k'' E_t\left[\hat{\mu}_{n,t+1}\right]\end{aligned}$$

12. Households, physical capital utilization:

$$\widehat{u}_t^k = \widehat{\widetilde{r}}_t^k \frac{1}{\sigma_A}$$

13. Households, physical capital accumulation:

$$\widehat{\bar{k}}_t = \frac{1-\delta_k}{M_n}(\widehat{\bar{k}}_{t-1} - \hat{\mu}_{n,t}) + \frac{i}{\bar{k}}\left(\widehat{i}_t + \widehat{\zeta}_{I,t}\right)$$

14. Households, knowledge capital:

$$\begin{aligned}0 &= -\widehat{q}_t^n - \widehat{\lambda}_{n,t} - \widehat{\zeta}_{c,t} + E_t\left[\frac{\beta \widehat{j}_{t+1}\left(\delta_n + r^n - 2\xi + \phi_1 - 1\right)}{\left(\bar{n}-1\right) M_n}\right. \\ &- \frac{\beta \widehat{\mu}_{n,t+1}\left(-\bar{n}\delta_n + \xi\bar{n} + \bar{n} - r^n + \xi - \phi_1\right)}{\left(\bar{n}-1\right) M_n} \\ &+ \frac{\beta\left(-\delta_n + \xi + 1\right)\widehat{\zeta}_{c,t+1}}{M_n} + \frac{\beta\left(-\delta_n + \xi + 1\right)\widehat{\lambda}_{n,t+1}}{M_n} + \frac{\beta\xi\widehat{q}_{t+1}^a}{M_n} \\ &- \left.\frac{\beta\left(\delta_n - 1\right)\widehat{q}_{t+1}^n}{M_n}\right]\end{aligned}$$

15. Households, investment in knowledge capital:

$$\begin{aligned}0 &= \widehat{q}_t^n - \Psi_n'' M_n^2 (1+\beta)\,\widehat{s}_t + \widehat{\zeta}_{S,t} - \Psi_n'' M_n^2 \hat{\mu}_{n,t} \\ &+ \Psi_n'' M_n^2 \widehat{s}_{t-1} + \beta M_n^2 \Psi_n'' E_t\left[\widehat{s}_{t+1}\right] + \beta M_n^2 \Psi_n'' E_t\left[\hat{\mu}_{n,t+1}\right]\end{aligned}$$

16. Households, knowledge capital accumulation:

$$\frac{\bar{n}\hat{s}_t\left(M_n+\delta_n-1\right)}{M_n}+\frac{\bar{n}\left(\delta_n-1\right)\hat{\mu}_{n,t}}{M_n}-\frac{\bar{n}\left(\delta_n-1\right)\hat{\hat{n}}_{t-1}}{M_n}-\bar{n}\hat{\hat{n}}_t=0$$

17. Households, adopted knowledge capital:

$$\left(1-\rho_{\zeta_C}\right)\widehat{\zeta}_{C,t}+\widehat{\lambda}_{n,t}=E_t\widehat{\lambda}_{n,t+1}+E_t\widehat{R}^n_{t+1}-E_t\widehat{\pi}_{t+1}-E_t\widehat{\mu}_{n,t+1}$$

18. Return on adopted knowledge capital:

$$\begin{aligned}0 \;\; = \;\; & \Pi\Bigg(-\frac{j\widehat{\mu}_{n,t}M_n\left(j\xi\left(\bar{n}-1\right)^2H''M_n+\bar{n}\right)}{\bar{n}-1}-\frac{j\widehat{j}_tM_n\left(j\xi\left(\bar{n}-1\right)^2H''M_n+\bar{n}\right)}{\bar{n}-1}\\ - \;\; & \frac{j\widehat{\bar{n}}_{t-1}\bar{n}M_n}{\bar{n}-1}-\widehat{q}^a_t\left(jM_n+\xi-\phi_1\right)-\widehat{q}^a_{t-1}\left(-jM_n+r^n-\xi+\phi_1\right)\\ + \;\; & \widehat{\pi}_t\left(-jM_n+r^n-\xi+\phi_1\right)-\widehat{R}^n_t\left(-jM_n+r^n-\xi+\phi_1\right)+\widehat{r}^n_tr^n\Bigg)\end{aligned}$$

19. Households, investment in adoption:

$$j\widehat{\mu}_{n,t}\xi\left(\bar{n}-1\right)H''M_n+j\widehat{j}_t\xi\left(\bar{n}-1\right)H''M_n+\frac{\bar{n}\widehat{\bar{n}}_{t-1}}{\bar{n}-1}+\widehat{q}^a_t=0$$

20. Households, adopted knowledge capital utilization:

$$\widehat{u}^n_t=\widehat{\bar{r}}^n_t\frac{1}{\sigma_n}$$

21. Households, adopted knowledge capital accumulation:

$$\frac{-\widehat{\bar{n}}_{t-1}\left(M_n+\xi-\phi_1\right)+(1-j)\widehat{\mu}_{n,t}M_n-j\widehat{j}_tM_n}{M_n}=0$$

22. Government expenditure:

$$\hat{g}_t=\rho_g\hat{g}_{t-1}+\sigma_g\epsilon_{g,t}$$

23. GDP:

$$\widehat{y}_t^G = \frac{c}{y^G}\widehat{c}_t + \eta_G \widehat{g}_t + \frac{i}{y^G}\left(\widehat{i}_t - \widehat{\zeta}_{\Upsilon,t}\right) + \frac{s}{y^G}\widehat{s}_t$$

where $\eta_G = G/Y^G$.

24. Resource constraint:

$$\begin{aligned} c\widehat{c}_t + i\left(\widehat{i}_t - \widehat{\zeta}_{\Upsilon,t}\right) + s\widehat{s}_t + \eta_G y \widehat{g}_t \quad = \quad & (y+F)\left[(1-\alpha)\left(a_t + \widehat{L}_t\right) + \alpha \widehat{\overline{k}}_{t-1} - \widehat{\mu}_{n,t}\right] \\ & + \left[(y+F)\,\alpha - r^k \overline{k} M_n^{-1}\right]\frac{1}{\sigma_A}\widehat{\widetilde{r}}_t^k \\ & + \left[(y+F)\,(1-\alpha) - r^n M_n^{-1}\right]\frac{1}{\sigma_n}\widehat{r}_t^n - j\widehat{j}_t \end{aligned}$$

25. Monetary Policy:

$$\widetilde{R}_t = \rho_R \widetilde{R}_{t-1} + (1-\rho_R)\left[\phi_\pi \widehat{\pi}_t + 4\phi_{dy}\left(\widehat{y}_t^G - \widehat{y}_{t-1}^G + \widehat{\mu}_{n,t}\right)\right] + \sigma_R \epsilon_{R.t}$$

26. Three equations describing the shocks to $\zeta_{S,t}$, $\zeta_{C,t}$ and $\zeta_{I,t}$:

$$\log(\zeta_{X,t}) = \rho_{\zeta X}\log(\zeta_{X,t-1}) + \sigma_{\zeta X}\varepsilon_{\zeta_X,t}$$

27. Productivity shock:

$$a_t = (1-\rho)a^\star + \rho_a a_{t-1} + \sigma_a \epsilon_{a,t}$$

28. Markup:

$$\log(\lambda_{f,t}) = \left(1-\rho_{\lambda_f}\right)\log(\lambda_f) + \rho_{\lambda_f}\log(\lambda_{f,t-1}) + \sigma_{\lambda_f}\epsilon_{\lambda_{f,t}}$$

Appendix B. Data

The sample is from 1980 to 2013. Firms' balance sheet data is from COMPUSTAT. We follow Brown, Fazzari, and Petersen (2009) to define high-tech industries. We divide the sample into two categories: high-tech industries and non-high-tech industries. High-tech industries have SIC codes 28, 357, 366, 367, 382, 384, and 737. We define gross cash flow, R&D, new share issues and total assets as (COMPUSTAT code in parentheses):

- Cash Flow is Depreciation and Amortization (DP) plus Income Before Extraordinary Items (IB) plus Research and Development Expense (XRD).
- R&D is Research and Development Expense (XRD).
- New Share Issues is Sale of Common and Preferred Stock (SSTK) minus Purchase of Common and Preferred Stock (PRSTKC).

The data is deflated using the CPI index from CRSP (expressed in 2000 dollars). For the non-high-tech-firms we exclude utilities (SIC code 49) and financial services firms (SIC code 6).

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Parameter	Mean	5%	95%	Type	Mean	St.dev.
ϕ_π	1.3564	1.2550	1.4446	N	2	0.6
$\phi_{\Delta y}$	0.1276	0.1019	0.1560	G	0.3	0.15
ρ_R	0.8074	0.7869	0.8271	B	0.6	0.2
ι_w	0.0905	0.0234	0.1868	B	0.5	0.2
Ψ_n''	38.2010	34.7480	40.7480	G	15	10
Ψ_k''	2.7882	2.289	3.2772	G	4	3
σ_k	4.7006	3.0015	6.9882	G	1.5	1
σ_n	1.2041	0.8123	1.6437	G	1.5	1
ζ_p	0.6616	0.6233	0.6913	B	0.5	0.2
ι_p	0.0347	0.0137	0.0599	B	0.5	0.2
η	0.0326	0.0167	0.0543	B	0.2	0.1
ζ_w	0.8551	0.8066	0.8999	B	0.5	0.2
ξ	0.0067	0.0054	0.0081	B	0.1	0.05
ϕ_1	0.7926	0.6826	0.8869	B	0.9	0.05
ρ_{ζ_i}	0.9541	0.9336	0.9701	B	0.5	0.2
ρ_{ζ_c}	0.1838	0.0897	0.2781	B	0.5	0.2
ρ_{λ_f}	0.9975	0.9952	0.9991	B	0.5	0.2
ρ_{ζ_S}	0.6932	0.6316	0.7690	B	0.5	0.2
ρ_{ζ_a}	0.8626	0.7867	0.9379	B	0.5	0.2
ρ_χ	0.9231	0.8912	0.9473	B	0.5	0.2
λ_w	0.1471	0.1176	0.1793	G	0.15	0.02
L^*	100.6000	99.8580	101.2400	N	100	2.5
$100\pi^*$	0.5294	0.4458	0.6096	N	0.5	0.05
$100(\beta^{-1}-1)$	0.1869	0.1379	0.2305	G	0.25	0.05
Φ_c	0.9247	0.9172	0.9324	B	0.7	0.2
$\lambda_f - 1$	0.6434	0.5157	0.7888	G	0.35	0.1
δ_k	0.0214	0.0169	0.0267	B	0.03	0.02
δ_n	0.0038	0.0023	0.0055	B	0.05	0.02
a^*	-2.2325	-2.5294	-2.0253	U	-100	100
H''	263.0200	262.5600	263.3100	G	250	100
α	0.2669	0.2385	0.2986	B	0.35	0.05
σ_L	0.8367	0.4405	1.3086	G	1.5	0.75
$100\sigma_R$	0.2178	0.2009	0.2358	IG	0	0
$100\sigma_{\zeta_i}$	3.4596	3.0152	3.8953	IG	0	0
$100\sigma_{\zeta_c}$	5.0367	4.7571	5.4850	IG	0	0
$100\sigma_{\lambda_f}$	0.1492	0.1297	0.1799	IG	0	0
$100\sigma_\Upsilon$	0.7111	0.6635	0.7611	IG	0	0
$100\sigma_{\zeta_s}$	12.8490	9.6719	14.9430	IG	0	0
$100\sigma_{\zeta_a}$	0.5981	0.5474	0.6537	IG	0	0
$100\sigma_{\zeta_g}$	3.0493	2.7669	3.5104	IG	0	0
$100\sigma_\chi$	7.6093	4.7102	12.327	IG	0	0
$100\sigma_w$	0.6487	0.5955	0.7062	IG	0	0

Table 1: Posterior means, 90% error bands, and priors of the model parameters.

	Long	Medium	Business
GDP growth	5.78 (4.73,7.4)	38.63 (35.71,41.68)	55.12 (51.56,58.25)
Inflation	12.01 (9.85,16.33)	42.93 (40.18,45.28)	44.39 (40.54,47.48)
FFR	20.14 (16.04,29.08)	60.69 (53.95,64.28)	18.66 (16.17,20.79)
Investment growth	0.94 (0.77,1.15)	48.38 (44.86,51.65)	50.62 (47.16,54.15)
Consumption growth	19.89 (17.12,23.54)	43.99 (41.62,46.19)	35.62 (31.93,39.21)
R & D growth	11.79 (10.22,13.66)	62.08 (59.07,65.1)	26.02 (22,29.82)
Wages growth	17.85 (14.91,21.77)	35.71 (33.56,37.98)	45.9 (41.78,49.76)
Hours	34.88 (30.73,40.7)	59.77 (54.33,63.94)	5.14 (4.12,6.23)
TFP growth	15.62 (12.58,20)	16.55 (13.96,19.57)	66.81 (62.15,71.03)
Endogenous TFP growth	25.66 (20.64,32.33)	24.14 (21.69,26.83)	49.66 (44.78,53.57)
Adopted knowledge growth	78.7 (75.13,82.59)	20.26 (16.09,24.07)	0.76 (0.4,1.65)
Knowledge growth	76.13 (72.42,80.41)	23.65 (19.4,27.35)	0.22 (0.16,0.29)

Table 2: Median and 90% error bands for the model-implied variance across different frequency intervals. Long term: Cycles of more than 50 years. Medium term cycle: Cycles between 8 and 50 years, Business cycle: Cycles between .5 and 8 years.

Business Cycle	MEI	Preferences	Mark-up	MER&D	Stationary tech.	Labor supply
GDP growth	34.942 (31.108,38.754)	4.119 (3.546,4.78)	13.575 (11.026,16.374)	0.008 (0.005,0.013)	1.649 (1.169,2.258)	9.875 (6.979,13.309)
Inflation	10.142 (6.926,13.222)	0.195 (0.101,0.357)	45.349 (38.222,52.829)	0.036 (0.020,0.065)	11.031 (9.006,13.322)	31.335 (25.436,37.726)
FFR	41.291 (37.419,44.885)	0.849 (0.650,1.093)	10.437 (8.593,12.441)	0.025 (0.013,0.049)	2.955 (2.283,3.736)	9.534 (7.529,12.000)
Investment growth	65.136 (60.314,69.519)	0.035 (0.015,0.069)	13.116 (10.496,16.285)	0.024 (0.015,0.039)	2.113 (1.526,2.758)	8.604 (5.706,12.315)
Consumption growth	0.924 (0.567,1.876)	62.990 (59.262,66.751)	15.928 (12.952,19.165)	0.002 (0.001,0.005)	0.778 (0.505,1.311)	13.854 (10.404,18.13)
R & D growth	1.822 (1.353,2.629)	0.013 (0.004,0.028)	1.105 (0.467,2.215)	73.139 (68.414,77.452)	0.723 (0.373,1.425)	19.981 (15.498,24.408)
Wages growth	4.592 (3.407,6.046)	0.681 (0.343,1.348)	80.995 (76.719,84.260)	0.002 (0.001,0.003)	8.544 (6.417,11.358)	3.807 (2.561,5.649)
Hours	39.037 (34.751,43.606)	1.24 (0.935,1.551)	4.007 (2.555,5.976)	0.006 (0.004,0.011)	15.133 (12.811,17.659)	24.302 (18.122,30.851)
TFP growth	9.570 (7.345,12.016)	1.265 (1.007,1.601)	17.405 (14.462,21.313)	0.007 (0.004,0.011)	60.801 (54.194,67.493)	2.144 (1.417,3.170)
Endogenous TFP growth	20.839 (18.089,24.022)	2.755 (2.350,3.346)	39.010 (34.027,43.451)	0.015 (0.009,0.025)	14.540 (12.698,16.607)	4.768 (3.412,6.471)
Adopted knowledge growth	6.715 (3.14,11.385)	0.102 (0.039,0.183)	43.135 (31.486,53.381)	7.339 (2.264,19.458)	1.883 (1.381,2.456)	13.098 (9.470,18.414)
Knowledge growth	4.255 (3.273,5.708)	0.015 (0.005,0.032)	1.332 (0.541,2.700)	61.382 (55.182,67.409)	0.898 (0.451,1.805)	28.082 (21.980,34.434)
Medium Term Cycle	MEI	Preferences	Mark-up	MER&D	Stationary tech.	Labor supply
GDP growth	41.933 (35.959,48.362)	0.226 (0.176,0.282)	16.218 (12.578,19.989)	0.069 (0.043,0.112)	1.282 (0.692,2.352)	34.402 (26.812,41.433)
Inflation	38.311 (28.639,47.936)	0.302 (0.225,0.406)	13.467 (9.579,18.407)	0.080 (0.036,0.172)	2.279 (1.374,3.754)	40.854 (32.796,49.867)
FFR	81.952 (77.629,85.038)	0.359 (0.267,0.476)	2.695 (2.092,3.387)	0.144 (0.080,0.264)	0.567 (0.332,1.017)	8.297 (5.890,11.971)
Investment growth	62.399 (56.479,67.862)	0.011 (0.006,0.023)	9.720 (7.442,12.348)	0.083 (0.053,0.133)	1.212 (0.665,2.049)	22.892 (17.419,28.918)
Consumption growth	30.116 (24.531,37.308)	2.363 (1.940,2.851)	25.584 (20.465,30.670)	0.053 (0.034,0.087)	0.785 (0.377,1.737)	37.274 (28.258,46.097)
R & D growth	39.607 (32.329,48.769)	0.008 (0.004,0.018)	2.552 (1.461,4.265)	9.654 (6.977,12.925)	0.699 (0.292,1.747)	43.768 (33.680,52.628)
Wages growth	27.817 (23.160,33.068)	0.021 (0.012,0.036)	53.725 (46.812,59.472)	0.131 (0.084,0.207)	2.010 (1.210,3.576)	14.240 (10.965,18.584)
Hours	48.234 (41.630,55.144)	0.274 (0.206,0.358)	3.479 (2.320,4.902)	0.085 (0.053,0.140)	0.598 (0.376,1.029)	40.122 (32.211,47.632)
TFP growth	22.151 (17.744,26.932)	0.195 (0.154,0.243)	39.078 (32.758,44.993)	0.751 (0.459,1.226)	10.623 (6.759,16.165)	21.855 (16.897,27.87)
Endogenous TFP growth	24.604 (20.352,29.558)	0.218 (0.174,0.269)	43.737 (36.519,50.241)	0.840 (0.508,1.386)	0.941 (0.518,1.726)	24.483 (19.135,30.727)
Adopted knowledge growth	45.559 (37.109,55.854)	0.008 (0.004,0.018)	3.060 (1.760,5.472)	3.971 (2.752,5.675)	0.493 (0.200,1.391)	43.451 (32.446,53.119)
Knowledge growth	45.834 (37.759,55.785)	0.005 (0.002,0.012)	3.144 (1.902,4.994)	3.837 (2.676,5.421)	0.568 (0.228,1.521)	43.484 (32.600,53.025)

Table 3: Median and 90% error bands for the variance decomposition. Top panel: Decomposition of the variance at business cycle frequencies (between .5 and 8 year). Lower panel: Decomposition of the variance corresponding to medium term cycle frequencies (between 8 and 50 years).

Figure 1: TFP Growth

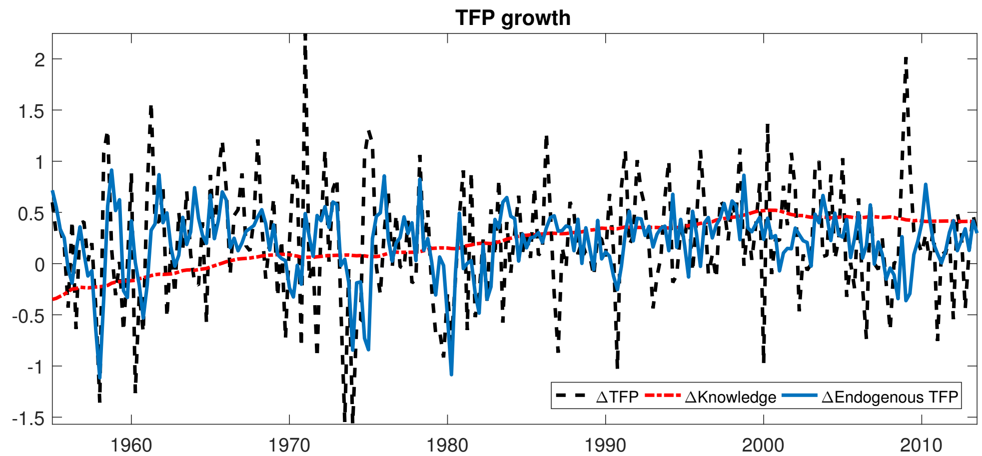
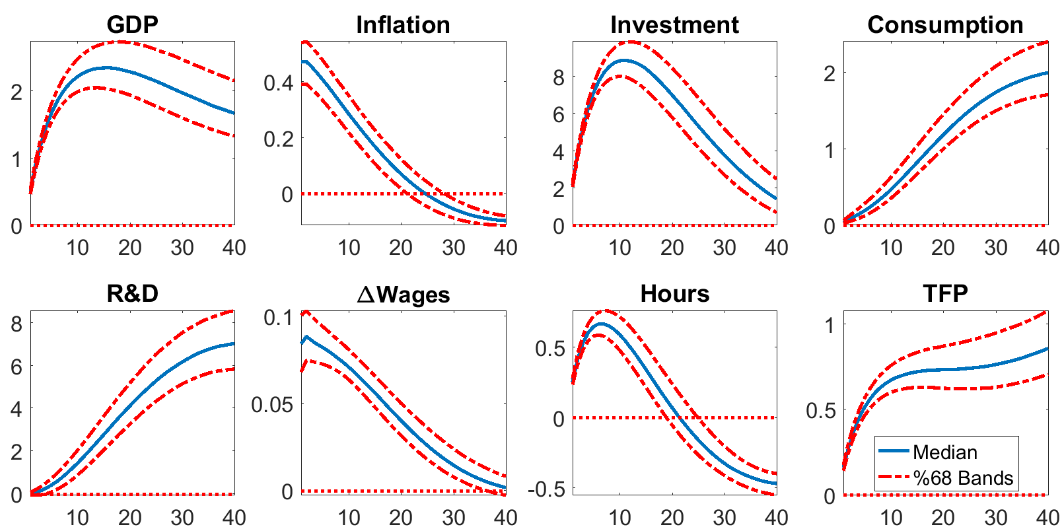


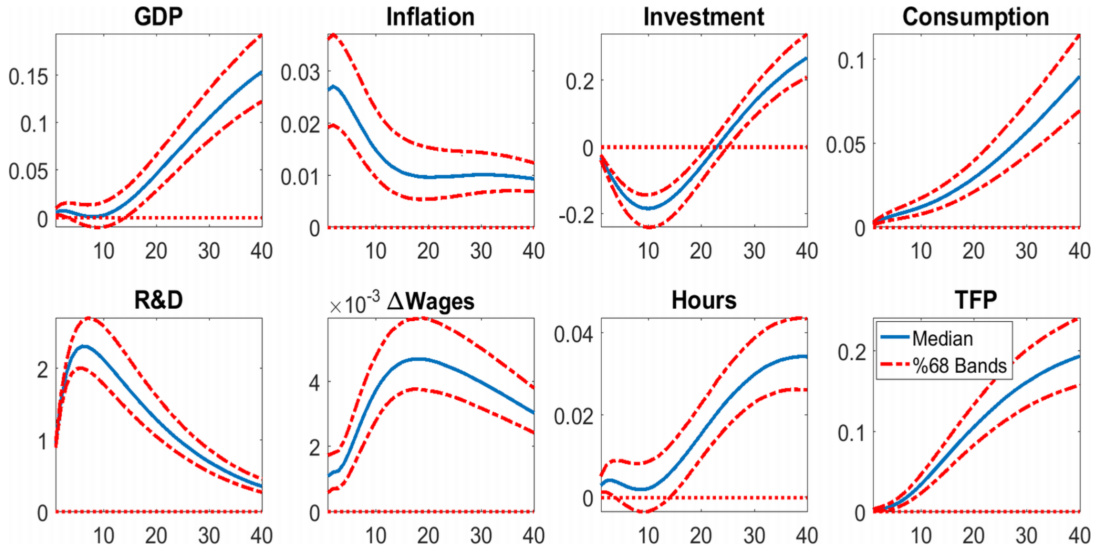
Figure 1 describes the evolution of TFP growth, knowledge, and endogenous TFP.

Figure 2: Shock to the Marginal Efficiency of Investment



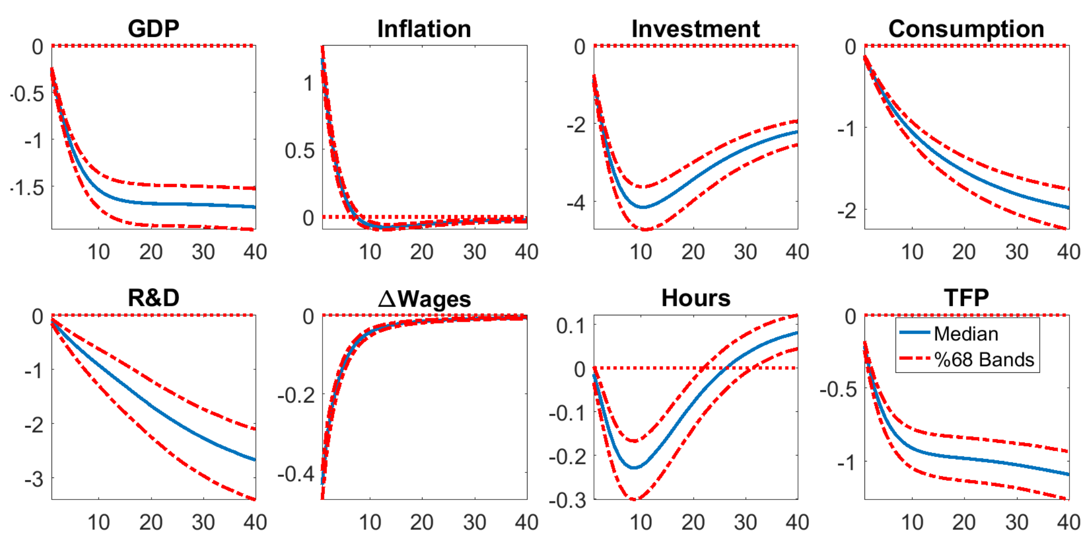
This figure displays impulse response functions for GDP, inflation, investment, consumption, R&D, change in wages, hours, and TFP to a positive shock to the marginal efficiency of investment. The solid line corresponds to the median while the dashed lines correspond to the 68% error bands.

Figure 3: Shock to the Marginal Efficiency of R&D



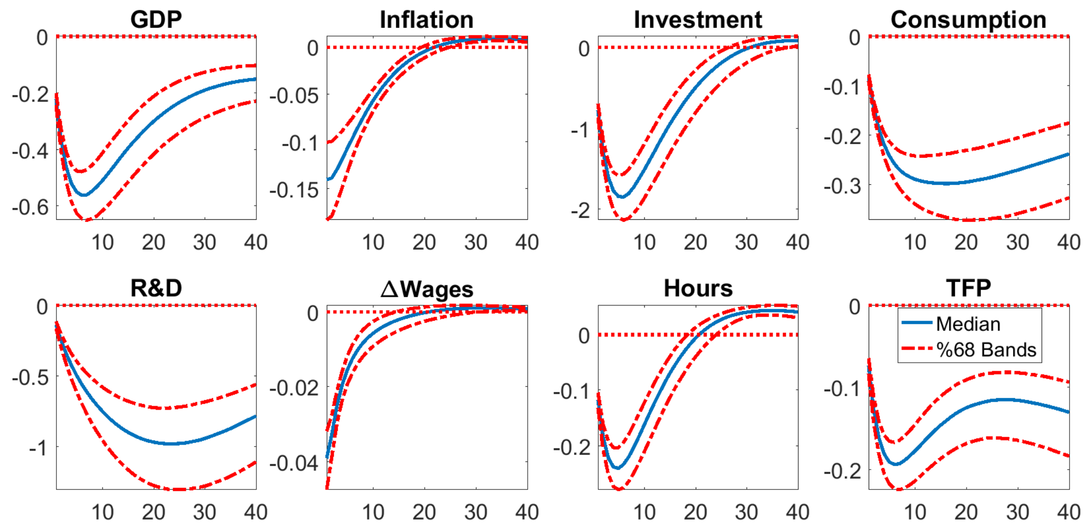
This figure displays impulse response functions for GDP, inflation, investment, consumption, R&D, change in wages, hours, and TFP to a positive shock to the marginal efficiency of R&D. The solid line corresponds to the median while the dashed lines correspond to the 68% error bands.

Figure 4: Shock to Markup



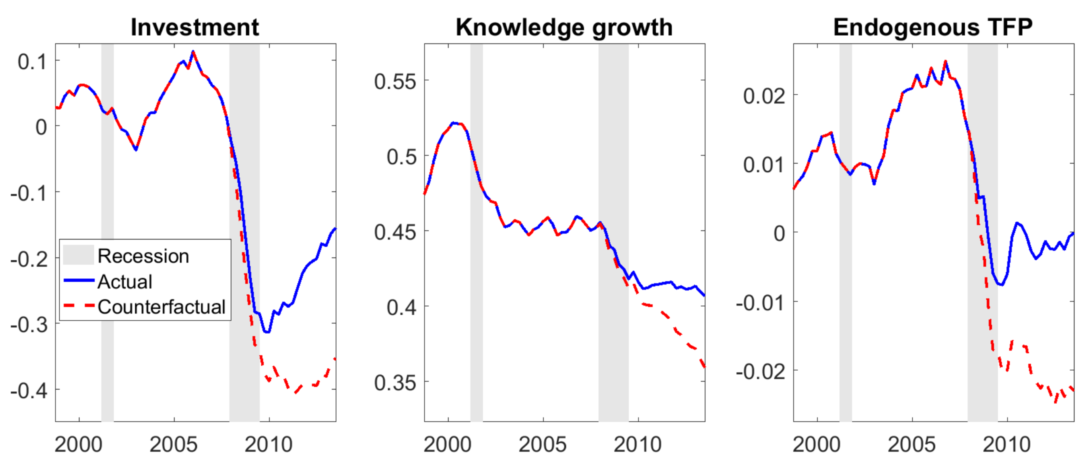
This figure displays impulse response functions for GDP, inflation, investment, consumption, R&D, change in wages, hours, and TFP to a positive shock to markup. The solid line corresponds to the median while the dashed lines correspond to the 68% error bands.

Figure 5: Monetary Policy Shock



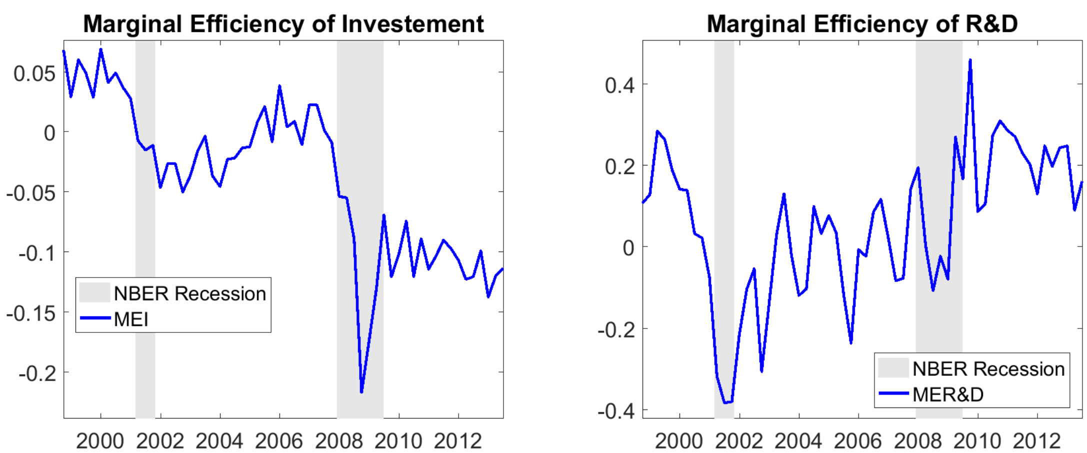
This figure displays impulse response functions for GDP, inflation, investment, consumption, R&D, change in wages, hours, and TFP to a contractionary monetary policy shock. The solid line corresponds to the median while the dashed lines correspond to the 68% error bands.

Figure 6: Impact of the Great Recession



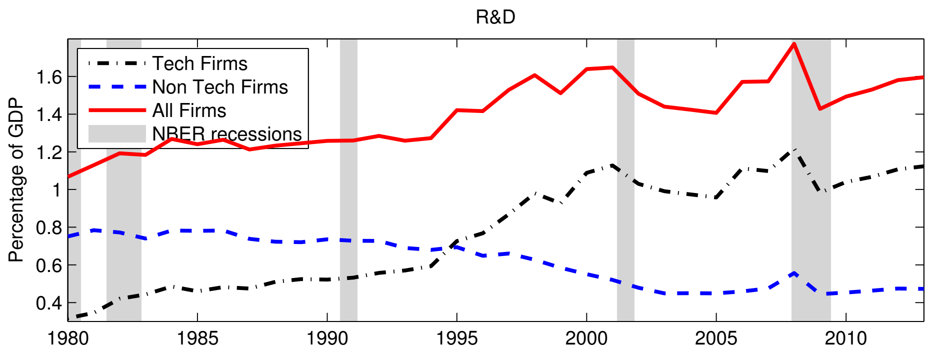
This figure analyzes the Great Recession through the lens of our model. The solid blue line reports smoothed estimates at the posterior mode for Investment, knowledge growth, and the endogenous part of TFP over the past 15 years. The red dashed line corresponds to a counterfactual simulation in which monetary and fiscal shocks are removed starting from the first quarter of 2008.

Figure 7: Marginal Efficiency of Investment and Marginal Efficiency of R&D

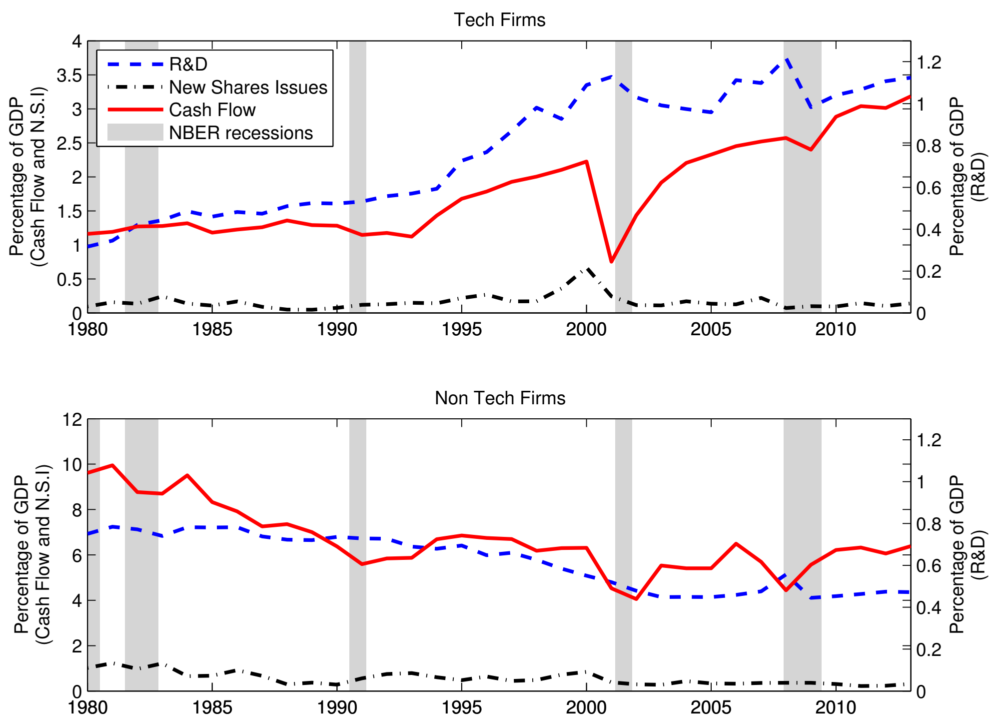


This figure analyzes the 2001 and 2008 recessions through the lens of our model. The solid blue line reports smoothed estimates at the posterior mode for the marginal efficiency of investment and marginal efficiency of R&D over the past 15 years.

Figure 8: Financing of R&D for High Tech and Non-High Tech Firms



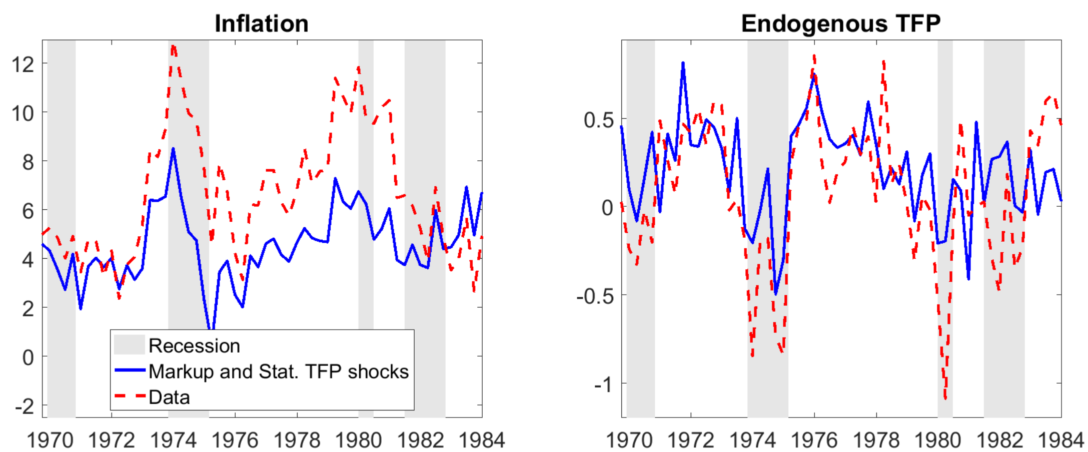
(a) R&D for all firms, tech firms, and non tech firms



(b) R&D, cash flow, and new shares issues for tech and non tech firms

This figure depicts the financing and R&D patterns for tech firms and non tech firms. In Panel (a), the solid red line reports R&D investment as percentage of GDP for all firms. The the dash-dot black line and dashed blue line show R&D investment as percentage of GDP for tech and non tech firms, respectively. Panel (b) reports cash flow, R&D and new shares issues for tech firms (first figure) and non tech firms (second figure). The red solid line shows cash flow as percentage of GDP, the dashed blue line depicts R&D investment (as percentage of GDP) and the dash-dot black line shows new share issues (as percentage of GDP).Tech firms are firms with the SIC code: 283, 357, 366, 367, 382, 384 or 737.

Figure 9: The Great Inflation



This figure analyzes the Great Inflation through the lens of our model. In the left panel, the red dashed line represents actual inflation, while in the right panel, the red dashed line corresponds to the smoothed estimate of the growth rate of the endogenous part of TFP at the posterior model. In both panels, the blue solid line corresponds to a counterfactual simulation in which all shocks, but the markup and the stationary technology shock, are set to zero.