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Citation for final published version:

Artuç, Erhan and Pourpourides, Panayiotis M. 2014. R&D and aggregate fluctuations. Journal of Economic Dynamics and Control 47 , pp. 54-71. 10.1016/j.jedc.2014.07.006

Publishers page: http://dx.doi.org/10.1016/j.jedc.2014.07.006

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R&D and Aggregate Fluctuations*

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July 12, 2014

Abstract

Empirical observations raise interesting questions regarding the sources of the excessive volatility in the R&D sector as well as the nature of the relation between the sector and aggregate fluctuations. Using US data for the period 1959-2007, we identify sectoral technology and capital investment-specific shocks by employing a Vector Autoregression. The identifying assumptions are motivated by a two-sector dynamic general equilibrium model. Controlling for real and nominal factors, we find that capital investment-specific shocks explain 70 percent of fluctuations of R&D investment, while R&D technology shocks explain 30 percent of the variation of aggregate output, net of R&D investment. Technology shocks jointly explain almost all the variation of output in the R&D sector and 78 percent of the variation of output in the rest of the economy. They also constitute the main factor of the procyclicality of R&D investment.

JEL Classification Codes: C13; C32; C68; E32; O3
Keywords: Cycles; Technology Shocks; Investment-specific Shocks; R&D; VAR

*We would like to give special thanks to Raymond Wolfe (National Science Foundation) for information and help with the data and to Jane Zhang (World Bank) for editorial comments. We thank seminar and conference participants at Cardiff University, the University of Cyprus and the Canadian Economic Association in Calgary. We also thank the anonymous referee for their useful comments and constructive suggestions which helped us to improve the paper. A supplementary Appendix is available as a separate document. The views in this paper are the authors and not those of the World Bank. All errors are our own.

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1 Introduction

The research and development (henceforth R&D) sector is considered one of the main driving forces of sustainable growth in the long run. However, investment in R&D as well as employment in the R&D sector exhibit substantial fluctuations relative to those of aggregate production and aggregate employment. Contrary to the Schumpeterian view, R&D appears to be procyclical in the data. These facts raise interesting questions regarding the sources of the excessive volatility, and the nature of the relation between the R&D sector and aggregate fluctuations. The purpose of this paper is to examine the impact of technology shocks on the R&D sector, as well as the contribution of the sector to annual fluctuations.

The previous literature has found that neutral technology shocks and shocks that improve the efficiency of newly produced capital are important sources of output fluctuations.[1] The identified technology shocks might be, to some extent, the result of R&D activities which were not modeled explicitly. It is also possible that some technology innovations emerging from R&D sectors are not well captured by the aggregate Solow residual and the real price of capital investment. This paper builds upon Fisher (2006), and introduces sectoral productivity and capital investment-specific shocks into a conventional two-sector dynamic stochastic general equilibrium (DSGE) model with R&D, which motivates three long-run identifying restrictions.

The identifying assumption for investment-specific shocks is the same as the one utilized by Fisher (2006), where the real price of capital investment is affected only by investment-specific shocks in the long-run. Unlike Fisher's model, the two-sector model implies two

[1] E.g. see Greenwood, Hercowitz and Krusell (2000), and Fisher (2006).

sectoral technologies which affect sectoral labor productivities in the long-run. The output in the R&D sector is used as an input in the production of the non-R&D output, but the reverse is not true. Therefore, we argue that it is reasonable to assume that, in the long-run, the output of the R&D sector (thus labor productivity), is affected only by R&D technology shocks and capital investment specific shocks. This long-run implication is used as an identifying restriction for R&D technology shocks. Then, technology shocks in the non-R&D sector are identified by imposing the restriction that in the long-run, labor productivity in the non-R&D sector is affected only by the three technology shocks. Following Fisher (2006), those restrictions are then imposed on a Vector Autoregression (VAR) to identify the shocks. The VAR is estimated using US macroeconomic time series along with data on R&D investment and GDP from the Bureau of Economic Analysis (BEA) and the National Science Foundation (NSF) satellite account for the period prior to 2008.

To quantify the impact of R&D on aggregate fluctuations, we first estimate a VAR using seven post-war annual time series. Similar to Fisher (2006), the shocks are identified by imposing long-run restrictions which are justified by the theoretical model. Data on R&D are only available at the annual frequency. Thus, we focus our analysis on those frequencies.[2] The plausibility of the empirical impulse responses are assessed by comparing them with the theoretical ones which are generated by the simple equilibrium model.

We find that capital investment-specific shocks play the largest role in driving the fluctuations of R&D investment while R&D productivity shocks affect considerably the fluctuations of output in the non-R&D sector. Our economic model demonstrates that factors that con-

[2]Comin and Gertler (2006) show that information extracted from annual data regarding medium-run fluctuations is virtually the same as that extracted from quarterly data.

tribute to the stock of R&D are not limited to the resources listed under R&D expenditures in the official accounts. While there can be direct additions to the stock of R&D within the R&D sector (identified from data on R&D expenditures), there can also be costly transfers from the non-R&D sector contributing to the stock of R&D. We show that the price of a transfer is inversely related to positive R&D shocks. As a result, an innovation in the R&D sector may induce a transfer of resources from the non-R&D sector as investment in the stock of R&D which, in turn, augments the production of the non-R&D output. Our calibration suggests that at the steady state such transfers are positive. Despite the fact that the size of the R&D sector is small, R&D specific shocks have a significant impact on aggregate fluctuations.

Our analysis designates that capital investment-specific shocks constitute the main source of fluctuations in R&D investment and improvements in productivity in the R&D sector induce a considerably positive impact on the output of the non-R&D sector. The variance decomposition implies that R&D productivity shocks explain 30 percent of the variation of output in the non-R&D sector. Non-R&D productivity shocks, on the other hand, play a smaller role in driving the fluctuations of output in the two sectors. We find that technology shocks jointly explain almost all the variability of output in the R&D. Among the three shocks, capital investment-specific shocks cause the biggest impact on hours for both sectors. Our results confirm Ouyang's (2011) findings, showing that technology shocks are important factors of the procyclicality of R&D since capital investment-specific and R&D productivity shocks, being the main sources of output volatility in the two sectors, induce output responses of the same sign.

In a separate exercise, we treat R&D solely as an expense according to the NIPA definitions and estimate a VAR which corresponds to a simplified one-sector version of our model. Doing so, we show that capital investment-specific shocks and neutral technology shocks generate similar results to previous studies. This exercise also signifies that if the R&D sector is excluded from the model and R&D is not treated as investment, the effect of technology shocks on hours is overstated to some extent.

There are a few theoretical papers in the literature showing the role of R&D in driving aggregate fluctuations. Comin and Gertler (2006), stress the significance of R&D, in generating medium-run fluctuations using an endogenous growth model. Butler and Pakko (1998) and Fátas (2000) demonstrate that R&D shocks improve the persistence of the dynamics of output and productivity.[3] Maliar and Maliar (2004) show that a DSGE model with R&D can account for the asymmetry in the shape of business cycles. However, R&D moves countercyclically in their model, which is at odds with observations in the data. Barlevy (2007), addresses this issue by arguing that R&D might be procyclical because of a dynamic externality inherent to R&D.

The empirical literature which relates R&D with fluctuations has been relatively more limited. Lach and Schankerman (1989) and Lach and Rob (1996) find that both R&D activities and capital investment are affected by a common shock which has very persistent effects. Geroski and Walters (1995) conclude that although aggregate demand affects innovation activity, it plays only a modest role as opposed to aggregate supply.

One issue in the literature is that there are no good measures of the contribution of

[3]Among others, see Braun and Nakajima (2009) also demonstrate the significance of R&D in a DSGE model.

R&D to technological improvements as they are reflected by the fluctuations of aggregate production. Patents might be an indicator of the inventive activity but they are not very explicit about the degree of the effect of R&D on macroeconomic fluctuations. Griliches (2000) argues that patent applications are usually taken early during research processes in expectation of long run gains. As a result, there is lag between granting a patent and actual innovation. Among others, Lach and Schankerman (1989) point out that advancements in science and technology have a direct impact on R&D spending. Griliches (1979) proposes the introduction of the stock of knowledge, approximated by past R&D expenditures, as an input in the production function.[4] Following them, we argue that potential shocks identified from fluctuations of R&D expenditures (investment) reflect precisely technological innovations resulting from R&D activities.

The rest of the paper is organized as follows. Section 2 presents evidence from data to underline the significance of R&D on fluctuations. Section 3 lays out the theoretical framework, and section 4 presents the stationary equilibrium, illustrates the identification of the structural shocks and presents theoretical impulse response functions. Section 5 describes the econometric approach in estimating the VAR and section and discusses the data. Section 6 presents and analyzes the empirical results from the VAR model. Section 7 concludes.

2 R&D and Aggregate Fluctuations

The R&D sector is a relatively small sector of the economy. For the period between 1959 and 2007, R&D investment is on average 2.7 percent of nominal GDP. Figure 1 displays the time

[4]This idea is also implemented by Doraszelski and Jaumandreu (2007).

series of R&D investment along with the NBER recessions (shadowed bars). Overall, R&D appears to be mildly procyclical as the correlation coefficient between the growth rate of real investment in R&D and real GDP is 0.53. Table 1 indicates that the growth rate of R&D investment is more than twice as volatile as the growth rate of real GDP while the growth rate of employment in R&D-performing firms is four times more volatile than the growth rate of aggregate employment. The correlation between employment in the R&D sector and employment in the non-R&D sector is quite low, with a correlation coefficient of -0.27, while employment volatility in the former is substantially higher than that in the latter. This suggests that not only there is a difference in the behavior of output and employment within sectors, there is also a difference in the behavior of employment between sectors.

These observations raise a number of interesting questions: What types of structural shocks cause the high volatility in the R&D sector? Is there a statistically significant link between the R&D sector and fluctuations in the rest of the economy? If so, what is the degree of contribution of the R&D sector in driving aggregate fluctuations? This paper attempts to shed some light on these matters within the context of an economic model which motivates three long-run identifying restrictions.

3 Economic Model

This section introduces a two-sector DSGE model. The purpose of the model is twofold: First, to derive the long-run identifying assumptions used in the empirical analysis, and second, to help us interpret the empirical results.

There are two productive sectors in the economy: the consumption good sector and the

R&D sector. The consumption sector produces good Y_{Ct}, which can be directly consumed, C_t or invested in the production of capital goods, I_{Ct}:

$$Y_{Ct} \geq C_t + I_{Ct}. \tag{1}$$

Output, Y_{Ct}, is produced via the constant-returns to scale production function

$$Y_{Ct} = A_t \left(R_t\right)^{\alpha_1} \left(K_{Ct}\right)^{\alpha_2} \left(H_{Ct}\right)^{1-\alpha_1-\alpha_2}, \tag{2}$$

where A_t is a measure of the sector's technology, K_{Ct} denotes the sector's beginning of period t capital stock, H_{Ct} is labor employed in the sector and $0 < \alpha_i < 1$. Input R_t is the stock of R&D which augments the production of the final good. It evolves according to the following law of motion:

$$R_{t+1} = \left(1 - \delta_R\right) R_t + D_t, \tag{3}$$

where D_t is an increment to the R&D stock and $0 < \delta_R \leq 1$. The growth rate of A_t is stochastic and denoted by $x_{At} = A_t/A_{t-1}$.

The R&D sector produces good Y_{Rt} which can be used in the production of the consumption good via D_t or invested in the production of capital goods, I_{Rt}:

$$Y_{Rt} \geq D_t + I_{Rt}. \tag{4}$$

Determination of D_t is discussed below and in the following section. Output, Y_{Rt}, is produced

via the constant-returns to scale production function

$$Y_{Rt} = J_t \left(K_{Rt}\right)^{\lambda} \left(H_{Rt}\right)^{1-\lambda}, \tag{5}$$

where J_t is a shock specific to the R&D sector, K_{Rt} denotes the sector's period t capital stock, H_{Rt} is labor and $0 < \lambda < 1$.[5] The stochastic growth rate of J_t is denoted by x_{Jt}.

There is a distinction between the physical capital used in the R&D sector and the physical capital used in the consumption-good sector. To capture differences in the nature of capital across the two sectors, we introduce technology $\kappa\Xi_t$, where $\kappa > 0$ is a scale parameter. This technology converts a unit of capital in the consumption-good sector into units of capital in the R&D sector. Note that the units of investment in capital of the R&D sector must be converted into units of investment of the consumption-good sector before new capital is produced: A time t unit of investment from the R&D sector corresponds to $\kappa\Xi_t$ units of consumption-good investment. As a result, capital is mobile between sectors but not on a one-to-one basis. Then, aggregate investment, $I_t > 0$, and aggregate capital stock, $K_t > 0$, are expressed as:

$$\begin{aligned} I_t &= I_{Ct} + \kappa\Xi_t I_{Rt}, \\ K_t &= K_{Ct} + \kappa\Xi_t K_{Rt}. \end{aligned} \tag{6}$$

[5]Notice that the model can be written in a way that production in the R&D sector is also augmented by the stock of R&D without affecting the long-run implications of the shocks on outputs presented by the proposition in section 4. This extension only makes the model more complex without any effects on the results and main conclusions. For this reason we have chosen to keep the economic model as simple as possible.

The accumulation equation for the stock of capital is given by

$$K_{t+1} = (1 - \delta_K) K_t + Z_t I_t, \tag{7}$$

where Z_t represents the time-t state of the technology for producing capital and $0 < \delta_K \leq 1$. The stochastic gross growth rate of Z_t is denoted by x_{Zt}. Efficiency requires that (1) and (4) hold with equality. Then, using the capital accumulation equation and (3.6) we can write the economy's budget constraint as follows:

$$\overline{P}_{Kt}\overline{K}_t + P_{Rt}D_t + C_t = Y_{Ct} + P_{Rt}Y_{Rt},$$

where $\overline{K}_t$ denotes the additional units of capital at the end of period t, and $\overline{K}_t \equiv K_{t+1} - (1 - \delta_K) K_t$. The budget constraint is similar to that assumed by Acemoglu and Zilibotti (2001), where investment in physical capital and investment in R&D are differentiated. Unlike the Acemoglu and Zilibotti model, we assume that only part of R&D output is used in the production of the consumption good. The price of output in the consumption-good sector is the numéraire, and $\overline{P}_{Kt}$ and P_{Rt} are the relative prices of capital and R&D respectively: $\overline{P}_{Kt}$ equals $1/Z_t$ and P_{Rt} equals $\kappa\Xi_t$. Technology Ξ_t is a function of technologies A_t, J_t and Z_t and its exact functional form is derived and analyzed in the following section.

The economy is inhabited by a representative household which consists of two members. One of the members is employed in the consumption-good sector while the other is employed in the R&D sector. The preferences of the household are defined over the household's

aggregate consumption, C_t, and the leisure of its two members, L_{Ct} and L_{Rt},

$$u\left(C_t, L_{Ct}, L_{Rt}\right) = \ln C_t + \varphi_C \ln L_{Ct} + \varphi_R \ln L_{Rt}, \tag{8}$$

where $L_{it} = 1 - H_{it}$ for $i = C,\ R$ and $\varphi_C,\ \varphi_R > 0$.[6] Then, the Pareto optimal equilibria are obtained from the central planning problem where the representative household maximizes its expected lifetime utility

$$E_0 \sum_{t=1}^{\infty} \beta^t u\left(C_t, L_{Ct}, L_{Rt}\right), \tag{9}$$

subject to (1), (2), (3), (4), (5), (6) and (7). The agent chooses C_t, H_{Ct}, H_{Rt}, K_{t+1}, R_{t+1}, I_{Ct}, I_{Rt}, D_t as well as the time t allocation of capital between the two sectors, K_{Ct} and K_{Rt}.

Let $\widehat{x}_t = dx_t/x$ denote the percentage deviation of x_t from its non-stochastic steady state. The processes that drive the exogenous shocks are given by the following vector autoregressive process:

$$\begin{gathered} \widehat{x}_{qt} = \rho_q \widehat{x}_{qt-1} + \varepsilon_{qt}, \ \text{ for } q = A,\ Z,\ J \\ \text{where } \ |\rho_q| < 1,\ \varepsilon_{qt} \sim iid\left(0, \sigma_q^2\right) \ \text{ with } E\left(\varepsilon_{pt}, \varepsilon_{qt}\right) = 0 \text{ for any } q \neq p. \end{gathered} \tag{10}$$

4 Stationary Equilibrium

We identify the three technology shocks by considering their effects over the long-run.[7] As we have shown in the previous section, the real price of investment is equal to the inverse of

[6]The specification of the utility function implies that labor is specific to each sector and is immobile between them. This feature of the model can be justified by evidence provided by Jovanovic and Moffitt (1990) that workers move mostly within sectors rather than across sectors. The VAR analysis that follows does not depend on whether labor is mobile or immobile between sectors.

[7]See Appendix 1 for the equilibrium conditions.

investment-specific technological progress.[8] Following Fisher (2006), the model derives the identifying assumption that in the long-run the real price of investment is only affected by investment-specific shocks (see also Altig et al., 2011). We would like to stress that we do not rule out the possibility of R&D-based innovations that improve the efficiency of capital. The argument is that R&D technological innovations do not affect the real (relative) price of investment in the long-run. The reason is that in the long-run, these innovations reduce both the nominal price of capital investment and the aggregate nominal price (numéraire), leaving long-run price ratio unaffected.[9] This implication follows from the assumed segregation of the R&D and capital sectors, that is justified from the fact that R&D is typically conducted in separate sectors. Potential long-run effects of R&D-based improvements in the efficiency of capital are captured by the permanent effects of R&D shocks on production.

Since part of the output in the R&D sector is employed as a production factor in the consumption-good sector, it follows that R&D technology shocks affect the output of the consumption good sector in the long-run, similar to the investment specific shocks. Essentially, consumption sector output is the final output in our setting, and it is affected from all technology shocks. However, the output of the consumption good sector is not a direct contributor in the production of the R&D output, therefore it is reasonable to conjecture that in the long run, the output in the R&D sector is affected only by R&D technology and investment-specific shocks. This enables us to scale the trending variables, eliminating steady state growth. The optimality conditions can then be expressed in terms of stationary

[8] See also Greenwood, Hercowitz and Krusell (2000), Cummins and Violante (2002) and Fisher (2006).

[9] In the empirical part of section 4, R&D-based innovations affect the real price of capital investment only in the short-run.

variables as demonstrated in the following proposition.

Proposition: *The resource constraints (1) and (4), the accumulation equations for the stock of R&D, (3), and capital, (7), and the optimality conditions (see Appendix 1), can be expressed in terms of only parameters and the stationary variables* y_{Ct}, y_{Rt}, k_{Ct}, k_{Rt}, k_t, i_{Ct}, i_{Rt}, c_t, d_t, r_t, x_A, x_J, x_Z, H_{Ct} and H_{Rt}, *where*

$$y_{Ct} = Y_{Ct}/\widetilde{X}_t,\ y_{Rt} = Y_{Rt}/X_t,\ k_{Ct} = K_{Ct}/\widetilde{X}_t Z_t,\ k_{Rt} = K_{Rt}/X_t Z_t,\ k_t = K_t/\widetilde{X}_t Z_t,$$
$$i_{Ct} = I_{Ct}/\widetilde{X}_t,\ i_{Rt} = I_{Rt}/X_t,\ c_t = C_t/\widetilde{X}_t,\ d_t = D_t/X_t \text{ and } r_t = R_t/X_t$$

with $X_t = (J_t)^{\frac{1}{1-\lambda}} (Z_t)^{\frac{\lambda}{1-\lambda}}$, $\widetilde{X}_t = (A_t)^{\frac{1}{1-\alpha_2}} (X_t)^{\frac{\alpha_1}{1-\alpha_2}} (Z_t)^{\frac{\alpha_2}{1-\alpha_2}}$ *and* $\Xi_t = \widetilde{X}_t/X_t$.[10]

Further below we show that the proposition implies intuitive relationships between the relative price of R&D, Ξ_t, and the stochastic processes A_t and J_t. The proposition indicates that at the steady state, the long-run output in the R&D sector, Y_{Rt}, and thus labor productivity in the R&D sector, are affected only by R&D and capital investment-specific technologies. Likewise, the proposition also implies that at the steady state the non-stationary variables in the R&D sector K_{Rt}, I_{Rt}, D_t and R_t are affected only by technologies J_t and Z_t. Let the growth rates of X_t and $\widetilde{X}_t$ be denoted by $e_t = (x_{Jt})^{\frac{1}{1-\lambda}} (x_{Zt})^{\frac{\lambda}{1-\lambda}}$ and $\widetilde{e}_t = (x_{At})^{\frac{1}{1-\alpha_2}} (e_t)^{\frac{\alpha_1}{1-\alpha_2}} (x_{Zt})^{\frac{\alpha_2}{1-\alpha_2}}$, respectively. Then, at the steady state, variables Y_{Rt}, I_{Rt}, D_t and R_t grow at the rate $e_t - 1$, variables Y_{Ct}, I_{Ct} and C_t grow at the rate $\widetilde{e}_t - 1$, variable K_{Rt} grows at the rate $e_t x_{Zt} - 1$ and variables K_{Ct} and K_t grow at the rate $\widetilde{e}_t x_{Zt} - 1$.

The stochastic processes have an effect on the relative price of R&D, which in turn affects

[10] The proof of the proposition is straightforward. A technical appendix with the derivations is available up request.

the distribution of resources between the consumption-good sector and the R&D sector. The proposition indicates that Ξ_t is the ratio of $\widetilde{X}_t$ to X_t, which implies that the relative (real) price of R&D can be written as $\kappa\Xi_t = \kappa\left(A_t\right)^{\tau_{\Xi,A}}\left(J_t\right)^{\tau_{\Xi,J}}\left(Z_t\right)^{\tau_{\Xi,Z}}$, where $\tau_{\Xi,A}$, $\tau_{\Xi,J}$ and $\tau_{\Xi,Z}$ are the elasticities of the relative price of R&D with respect to the stochastic growth rates A, J and Z: $\tau_{\Xi,A} = \frac{1}{1-\alpha_2}$, $\tau_{\Xi,J} = -\frac{(1-\alpha_1-\alpha_2)}{(1-\lambda)(1-\alpha_2)}$, $\tau_{\Xi,Z} = \frac{\alpha_2-\lambda(1-\alpha_1)}{(1-\lambda)(1-\alpha_2)}$.

Clearly, the effects of sector productivity shocks A and J on the relative price are positive and negative, respectively. Any positive (negative) effect on R&D resulting from an increase (decrease) in A is mitigated by the increase (decrease) in the relative price. Over the long-run however, A shocks have no effect on R&D. On the other hand, the sign of the effect of Z on the relative price depends on whether α_2 is greater or smaller than $\lambda\left(1-\alpha_1\right)$.

From the economy's budget constraint it is evident that, it is possible to transfer units of output from the consumption-good sector to the R&D sector, and vice versa; e.g. a unit of output from the consumption good sector corresponds to $1/P_{Rt}$ units of investment in the stock of R&D. Then, a positive productivity shock in the R&D sector ($\varepsilon_{Jt} > 0$) increases investment in the stock of R&D, not only because the same quantities of inputs produce more output in the R&D sector, but also because R&D becomes relatively cheaper as the relative (real) price of R&D (P_{Rt}) decreases. In other words, a positive R&D shock facilitates the conversion of units of output from the consumption-good sector into R&D stock. The fact that R&D becomes relatively cheaper along with the anticipation of future gains from R&D motivates the transfer of resources towards the R&D sector. This means that part of I_{Ct} can be invested in the stock of R&D (i.e. $I_{Ct} > I_t$). These transfers can be thought of as resources which increase the stock of human capital, either directly or indirectly. A

transfer may also include resources which are excluded from capital stock and are used to improve conditions in the workplace, hence improve productivity. Thus, a positive R&D shock may induce a flow of resources from the consumption-good sector to the R&D sector (as a contribution to the stock of R&D) to the extent that $D_t > Y_{Rt}$, which implies that $I_{Rt} < 0$ while $I_t > 0$. Note that those transferred resources may not be explicitly identified as R&D from the national accounts, because they are not listed under R&D expenditures. Therefore, despite the small size of the specialized R&D sector, R&D shocks may cause a significant variation in the output of the non-R&D sector, and as a result in aggregate output.

4.1 Calibration and the Theoretical Impulse Response Functions

We calibrate the model and present theoretical impulse responses to the shocks prior to the empirical analysis. As in Fisher (2006), those responses do not constitute a tool of identification of the shocks, but help us to motivate the analysis of the following section by assessing the plausibility of the responses identified from the data. One way to determine that the empirical impulse responses are correctly identified is by showing that under reasonable model parameter values the theoretical and the empirical responses exhibit a similar behavior.

To be consistent with the relative magnitudes of the sectors we observe in the data, we set the steady state share of R&D in total output to 3 percent.[11] In addition, we set the

[11] The aggregate output equation is $Y_t = Y_{Ct} + P_{Rt}Y_{Rt}$. Then, the share of R&D in output, $(P_{Rt}Y_{Rt})/Y_t$, can be written as $1 - 1/(Y/Y_{Ct})$. Due to the presence of the real price of R&D which has a steady state growth rate of $x_{At}^{\tau_{\Xi,A}} x_{Jt}^{\tau_{\Xi,J}} x_{Zt}^{\tau_{\Xi,Z}}$, the outputs in the two sectors can have different steady state grow rates while the share of R&D in output is fixed. It follows that a 3% share of R&D in output is roughly equivalent to setting $Y_t/Y_{Ct} = 1.03$. Using the latter, the aggregate output equation, rewritten as $\kappa(y_{Rt}/y_{Ct}) = (1.03) - 1$, is introduced as an additional equation in the system of steady state equations to ensure that the share of R&D in output is consistent with that observed in the data.

steady state growth rates of output in the R&D and non-R&D sectors equal to the average annual growth rates observed in the data over the sample period that is, $(e-1=)$ 3.6 percent and $(\widetilde{e}-1=)$ 1.8 percent, respectively. The share of labor in the consumption-good sector, $(1-\alpha_1-\alpha_2)$, is set to 0.64 while the shares of R&D, α_1, and capital, α_2, are set to 0.10 and 0.26, respectively.[12] The discount factor, β, is chosen to be 0.95 which is a value tyically used for annual frequencies. The steady state, x_Z, is set to 1.02 which corresponds to the average annual gross growth rate of the inverse of the real price of investment observed in the data over the sample period. The annual depreciation rate, δ_K, is choosen to be 0.10 which is consistent with the quarterly value of 0.025 used by Fisher (2006) and Altig et al. (2011). The weights of leisure in the utility function, φ_C and φ_R, are normalized to unity.[13] The persistence parameters ρ_A, ρ_Z and ρ_J are all set to 0.65 which corresponds to a value of 0.87 in the quarterly frequency. This value lies within the mid-range of values used in the RBC literature for persistence parameters. Since the R&D sector is labor intensive, we set the share of labor, $(1-\lambda)$, in the output of the sector to 0.9.[14] As noted by Hall (2007), and previously by Griliches (2000), the measurement of depreciation of R&D assets is the central unsolved problem in the measurement of the returns to R&D. Hall argues that determining the appropriate depreciation rate of R&D is difficult, if not impossible.[15] In this paper, we

[12]Those values lie within the range of values typically used in the literature examining aggregate production, and imply a reasonably small share of R&D in the production of the non-R&D sector. The baseline behavior of the impulse response functions are robust around those values.

[13]The restriction on the relative size of Y_C and Y_R also controls for the relative size of hours despite the fact that we normalize φ_C and φ_R to unity. Our benchmark calibration implies a ratio of steady state hours, H_R/H_C, of 7.6 percent.

[14]Most previous papers assume that R&D output is produced only by labor (e.g. Butler and Pakko, 1998, Braun and Nakajima, 2008). We allow for, at least, a small share of capital. The results are robust around this share value.

[15]According to Hall, the difficulty lies on at least two reasons. First, on the fact that at the micro level, the depreciation rate is endogenous to the behavior of each firm and its competitors, and second, on the fact that it is extremely difficult to determine the lag structure of R&D in generating returns. For a further

calibrate the model assuming two different values for the depreciation rate, $\delta_R = 0.5$ and $\delta = 0.8$. The scale parameter κ is pinned down at the steady state by the steady state equations. It is worth noting that the calibration implies that at the steady state, there is a positive transfer of resources from the non-R&D sector as a contribution to the stock of R&D (in addition to the contribution of the R&D sector). The parameter values are summarized in table 2.

Figure 2 plots the response of output and hours in each sector to one percent positive productivity shock in the R&D sector. The responses of output suggest that technology shocks in the R&D sector have a long-run impact on the production of both sectors. The response of R&D output is always positive, while the response of output in the consumption-good sector is positive after the first period, under $\delta_R = 0.8$. For the lower depreciation rate, the output of the consumption-good sector responds positively only after the fourth period indicating that the impact of an R&D shock becomes positive faster, the higher the depreciation rate. This is due to the fact that a lower depreciation rate of R&D creates an incentive for the agents to work relatively less. The lower depreciation rate induces a loss in the consumption utility which is compensated by a gain in leisure utility. Although a lower R&D depreciation rate induces a lower output than that of a higher depreciation rate, the underlying utility level of the household can be the same under the two regimes. The response of hours to a positive shock is positive when the intertemporal substitution effect dominates the wealth effect, and negative when the reverse holds. While the households are willing to exploit the gain from saving by substituting intertemporally away from leisure

discussion see Hall (2007).

today toward consumption in the future, they also tend to decrease work effort as they feel wealthier (wealth effect). Figure 2 indicates that the response of hours in the R&D sector is always positive only if the depreciation rate is high. The response of hours in the non-R&D sector is always negative, and smaller in magnitude the higher the depreciation rate.

Figure 3 displays the responses of output and hours to a negative capital investment-specific shock. The deterioration of investment-specific technology always induces negative responses in both sectors. In this case, the inter-temporal effects caused by the Z-shock clearly dominate the wealth effects. This result is also found in Fisher (2006) and Altig et al. (2011) who studied an aggregate sector economy. For the same reason as in the case of a productivity shock in the R&D sector, the responses to an investment-specific shock are larger for a lower R&D depreciation rate. Likewise, figure 4, shows that the responses of output and hours to a positive productivity shock in the non-R&D sector are positive at all times, indicating the dominance of inter-temporal substitution effects.

5 VAR Estimation and Data

In this section we embed the long-run implications of our economic model as identification restrictions on the parameters of the following VAR:

$$\mathbf{C}\mathbf{y}_t = \mathbf{\Psi}_1\mathbf{y}_{t-1} + \mathbf{\Psi}_2\mathbf{y}_{t-2} + \cdots + \mathbf{\Psi}_p\mathbf{y}_{t-p} + \varepsilon_t, \tag{11}$$

where $\mathbf{y}_t$ is a vector of time t variables, ε_t is a vector of time t structural shocks, with a diagonal variance-covariance matrix $E\left(\varepsilon_t\varepsilon_t'\right) = \mathbf{\Sigma}$, and $\mathbf{C}$ is a matrix that contains the

contemporaneous relations of the variables in $\mathbf{y}_t$ (with ones in the diagonal). Vector $\mathbf{y}_t$ contains seven variables: the real price of capital investment, labor productivities in the R&D and non-R&D sectors, per capita hours in the R&D and non-R&D sectors, the inflation rates and the nominal interest rate. Following Fisher (2006), the last two variables are included in order to capture potential effects of monetary policy. To sum up, the long-run restrictions imposed on the VAR are the following:

***Restriction 1*:** Only capital investment-specific shocks affect the real price of investment in the long-run.

***Restriction 2*:** Only capital investment-specific shocks and R&D shocks affect labor productivity in the R&D sector in the long-run.

***Restriction 3*:** Only capital investment-specific shocks, R&D shocks and consumption-sector shocks affect labor productivity in the consumption-good sector in the long-run.

Restrictions 1-3 correspond to the proposition, discussed in the previous section. [16] As shown in the appendix 3, we use distinct price deflators for capital investment, GDP and R&D such that the data for $\overline{P}_{Kt}$, Y_{Rt} and Y_{Ct} used in the empirical analysis are in accordance to the variables of the economic model.[17] It must be emphasized that, as the economic model suggests, in the short and medium-run, productivity shocks in the consumption-good sector

[16] Restriction 1 is identical to assumption 1 in Fisher (2006). Similarly, restriction 3, which essentially states that consumption sector output is only affected from technology shocks, is equivalent to assumption 2 in Fisher's paper.

[17] The right-hand side of the economy's budget constraint indicates that real GDP is $Y_{Ct} + P_{Rt}Y_{Rt}$. Then, nominal GDP is written as $P_{GDPt}Y_{Ct} + P^*_{Rt}Y_{Rt}$, where $P^*_{Rt} = P_{GDPt}P_{Rt}$ with P_{GDPt} denoting the GDP deflator. Likewise, nominal investment in capital is $P_{Kt}\overline{K}_t$, where $P_{Kt} = P_{GDPt}\overline{P}_{Kt}$. Having data on $P^*_{Rt}Y_{Rt}$ and price delfators P^*_{Rt}, P_{GDPt} and P_{Kt}, we obtain time series for Y_{Ct}, Y_{Rt} and $\overline{P}_{Kt}$ that correspond to the variables of the model. Further information is provided in Appendix 3.

may well affect production in the R&D sector. The estimation methodology follows Shapiro and Watson (1988) and Fisher (2006). The details are provided in Appendix 2.

5.1 Data used in the analysis

Measuring the output of R&D activity is a challenge because there is neither an observable market price nor a reported quantity of output for R&D. The latter is mainly produced by firms for internal use. A commonly used measure of R&D activity is expenditures in R&D, which constitute an investment that pays off in the long run. Currently, expenditures on R&D are not included as investment in GDP in the official accounts but instead they are treated as current period expenditures. Treating R&D as investment, rather than as intermediate expenditures, results in important changes to the calculation of GDP. In BEA's National Income and Product Account (NIPA), *business* R&D expenditures are included as intermediate rather than final expenditures, which means that they are not added up in deriving GDP. Other expenditures in R&D, which are included in the calculation of the GDP, cannot be separately identified from other components reported in the NIPA tables. Although those expenditures are included in GDP, they are not treated as investment so they are not subject to depreciation.

In 2006, the Bureau of Economic Analysis (BEA) jointly with NSF launched an R&D satellite account to explore investment in R&D and its larger economic effects. The BEA-NSF R&D satellite account provides a measure of the value of R&D output and adjusted GDP by transforming R&D expenditures into measures of real investment. Throughout our analysis, we use data from the R&D satellite account and deflate nominal R&D investment

using the output-based price index. Further information about the data can be found in Appendix 3.

In the spirit of Altig et al. (2011), the hours measure corresponds to sectoral employment multiplied by per capita hours in the sector, divided by population over 16 years old. The employment data in the R&D sector are obtained from the NSF survey.[18]. Since data on hours per worker in the R&D sector are not available, in our benchmark specification we approximate per capita hours with per capita hours in the non-farm business sector. Employment in the non-R&D sector corresponds to employment in the nonfarm business sector net of employment in the R&D sector. Thus, hours in the non-R&D sector are computed as sectoral employment multiplied by per capita hours in the nonfarm business sector, divided by the population measure.[19] Consequently, the difference in the variation of the benchmark measures of H_{Rt} over H_{Ct} is due to variation in employment.[20] It can be shown that, the annual growth rate of total hours and the annual growth rate of total employment are highly correlated displaying similar fluctuations which suggests that employment is the main driving force of total hours. For this reason, we also present *alternative measures* of H_{Rt} and H_{Ct}, computed simply as employment divided by population.[21]

Following Fisher (2006), the price index of capital investment, P_K, corresponds to the price of total investment. We construct the index using the equipment deflator along with the NIPA (National Income and Product Accounts) deflators for residential and nonresidential

[18]Additional information about the employment data can be found in Appendix 3

[19]Nonfarm business hours and employment are published by the Bureau of Labor Statistics (BLS).

[20]Previous studies also indicate that most variation in total hours is due to variation in employment than variation in individual hours (e.g. Hansen (1985), Castro and Coen-Pirani (2008)).

[21]The theory could also be summarized by an indivisible labor model a la Hansen (1985) and Rogerson (1988). In that case, the optimality conditions for labor supply in the theoretical model would be slightly different but the main theoretical arguments would remain unaffected.

structures, consumer durables and government investment. The equipment deflator was constructed by Gordon (1990) for the years up to 1980 and was extended by Cummins and Violante (2002) for the years up until 2000. We extend the Gordon-Cummins-Violante index further to 2007 using the pattern of NIPA investment price series. The rest of the data were taken from the NIPA tables. The price index, P_{GDPt}, used to deflate the price of capital investment is the implied deflator from chained real GDP. Aggregate output in the consumption good sector is nominal GDP net of R&D investment as reported in the BEA-NSF satellite account, deflated by the implied GDP deflator. Outputs Y_{Rt} and Y_{Ct} are obtained by dividing real R&D investment and real aggregate output in the consumption good sector by the population measure.[22]

In practice, labor productivities and the real price of capital investment are nonstationary. To overcome this problem, we follow the common practice of first differencing. The measures of per capita hours also exhibit some nonstationarity. This feature is also documented in previous studies that examine quarterly data (e.g. Francis and Ramey, 2005, Galí and Rabanal, 2005, and Fisher, 2006). The nonstationarity of per capita hours is even more evident at annual frequencies. As Fisher (2002) points out, the appropriate way to include per capita hours into the analysis is a matter of some controversy. Christiano, Eichenbaum and Vigfusson (2003) provide an extensive discussion on the treatment of per capita hours in the VAR. In this paper, we stationarize the hours measures by removing a linear trend from the log series. As in Collard and Dellas (2007), this approach avoids the criticism of Christiano et al. (2003), that hours should not be differenced. Using hours in levels or

[22] Aggregate real output in the consumption-good sector is defined as aggregate nominal output net of R&D investment divided by the implicit GDP deflator from the BEA-NSF satellite account.

first-differences produces confidence intervals for hours and other variables that diverge to infinity as the horizon increases.

The interest rate is measured by the effective federal funds rate and the inflation rate is defined as the growth rate of the consumer price index. In the empirical analysis, we employ US annual data for the period 1959-2007. We use annual frequencies because R&D investment and total employment of R&D performing companies are reported only at annual frequencies. Moreover, data on R&D investment and employment are available only after 1959 and 1958, respectively. Our sample excludes the turbulent period after 2007.

6 Empirical Results from the VAR

In this section we discuss our results from the estimated VAR. With quarterly data, four is the common choice for the number of lags which adequately captures the medium-run dynamics in the data.[23] This corresponds to one lag at annual frequencies. The one year lag is also a preferable choice given the size of the available sample. In what follows, first we examine the dynamic responses of outputs and hours of work to a productivity shock in the R&D sector, a productivity shock in the consumption-good sector and an investment-specific shock. Second, we examine the contribution of each of the three shocks and the R&D sector to the overall variability of the macroeconomic variables.

[23]For instance, see Christiano, Eichenbaum and Evans (2005), Altig, Christiano, Eichenbaum and Linde (2005) and Fisher (2006).

6.1 Impulse Response Functions

Figure 5 displays impulse response functions to a one standard deviation positive technology shock, ε_{Jt}, in the R&D sector. The two dashed lines correspond to 90 percent confidence intervals computed by non-parametric bootstrap.[24] An R&D technology shock induces a statistically significant positive increase in R&D output which gradually reaches a peak in 6 years after the occurrence of the shock. The response of output in the consumption-good sector becomes significantly positive only after the second year following the R&D shock, reaching a peak increase 6 years after the shock.[25] The responses take a long time to peak relative to the responses of technology shocks in Fisher (2006) where they peak after 3 years at most. The response of hours in the R&D sector is statistically insignificant, covering zero, while the response of hours in the non-R&D sector is statistically significant after the third year following the shock. In other words, R&D shocks have a positive impact on hours of only the non-R&D sector in the long-run.

Figure 6 demonstrates the big impact of changes in investment-specific technology on the fluctuations of R&D activity. A positive shock in the real price of capital investment induces a prolonged and statistically significant decrease in R&D output with a peak decline in 6 years. Investment-specific shocks have a large and statistically significant impact not only on the output of the R&D sector but also on the hours which respond negatively to a negative shock in Z_t. Hence, the responses suggest that an improvement in the technology

[24] Given the frequency and length of our data we have chosen to present 90 percent intervals. The 95 percent intervals are slightly wider but the main results still go through. The results are available upon request.

[25] Notice that the initial small and statistically insignificant effect of the R&D productivity shock on the output of the consumption-good sector is consistent with the structure of our economic model in which shocks specific to the R&D sector do not have a direct contemporaneous effect on the consumption-good sector output.

producing physical capital induces a considerable increase in R&D activity. Output and hours in the non-R&D sector exhibit negative responses to a negative shock in Z_t. However, those responses are marginally statistically significant while their magnitude suggests that the consumption-good sector is less sensitive to changes in investment specific technology than the R&D sector.

Figure 7 shows that the impulse response of output in the consumption-good sector to a type A shock is positive and hump-shaped, with a peak in the fourth year following the occurrence of the shock. The response of hours in the non-R&D sector is positive and statistically significant only after the third year. The hump-shape of the impulse responses functions of output and hours to technology shocks are also evident in Fisher (2006). However, in Fisher, the responses are negative initially for the first sample and peak sooner. The responses of output and hours in the R&D sector are statistically insignificant.[26]

6.2 Variance Decompositions

The qualitative similarities between the theoretical and empirical impulse responses functions provide some confidence that the structural shocks are correctly identified. In this subsection, we evaluate the contribution of each shock to the overall variability of the variables in our analysis by presenting two sets of variance decompositions. The first set corresponds to the direct contributions of the three shocks. In this set, variance decompositions are computed by non-parametric simulations of the VAR model.[27] Figure 8 displays the distributions of

[26]The empirical impulse response functions are roughly consistent with most of the main dynamics generated by the economic model. A more sophisticated version of the model may generate responses closer to the empirical ones, both in terms of magnitude and size. However, its role in this paper is auxiliary.

[27]Thev are computed in simulation blocks, separately for each shock

the variance decompositions for output and hours of work in each sector. The generated distributions draw an informative picture of the accuracy of the estimated contributions of the shocks. The properties of those distributions are such that they provide confidence that the means and the medians of the distributions can be taken as statistically accurate measures. Median values of variance decompositions along with 90 percent confidence intervals are reported in table 3 (the medians are close to the estimated means).

R&D technology shocks explain almost 20 percent of the variability of output in the sector and only a small percentage of the variability of the sector's working hours. Our estimates indicate that despite the fact that the R&D sector is small relative to the overall economy, the impact of R&D technology shocks on the output of the non-R&D sector is quite large as they account for about 30 percent of its variation. They also explain a non-negligible portion of the variance of hours in the non-R&D sector in the order of 17 percent. Our analysis shows that shocks to investment-specific technology are crucial to the variability of R&D investment, being the main driving force of output fluctuations as they explain almost 70 percent of its variance. Investment-specific shocks also explain almost 40 percent of the variance of the hours worked in the R&D sector. The impact of investment-specific shocks on the variance of output in the consumption-good sector is also considerable, but not as large as it appears to be in the R&D sector. Our results suggest that technology shocks in the non-R&D sector play only a minor role in driving the fluctuations of output and hours in the two sectors. As regards the variability of labor productivities, the highest fraction in the R&D and non-R&D sectors is attributed to investment-specific shocks.

Our results confirm Ouyang's (2011) claim that technology shocks are important factors

in explaining the procyclicality of R&D for two reasons. First, the three technology shocks are the main sources of output volatility in the two sectors as they jointly explain, on average, about 92 percent and 79 percent of the variance of outputs in the R&D sector and the rest of the economy, respectively. Second, capital investment-specific and R&D technology shocks which are the main contributors of output variability, induce statistically significant output responses of the same sign. The variance decompositions also indicate that technology shocks, jointly explain a moderate proportion of the variance of hours in the two sectors.

Table 4 displays variance decompositions when the R&D sector is not modeled as a separate sector and R&D is not treated as investment. In this case, aggregate output corresponds to the GDP reported in the NIPA tables while hours correspond to aggregate per capita hours (case when $\alpha_1 = 0$). These results show that under this specification of the model, investment-specific shocks and neutral technology shocks explain, on average, about 40 and 33 percent of the variability of NIPA output while the combined effect of technology shocks is about 90 percent. This result is not too different from Fisher (2006) who finds that that investment-specific shocks explain 42-67 percent of the variation of output while neutral technology shocks explain 8-33 percent.[28] However, direct comparison with Fisher (2006) is not straightforward because the results in his paper not only correspond to two sub-samples of quarterly frequency but also the total sample period does not exactly coincide with ours. It is worth noting that the combined effect of technology shocks on productivity and hours increases significantly compared to the model where there is a separate R&D sector and R&D is treated as investment.

[28] Altig et al. (2011) also find that capital investment-specific shocks explain 41 percent of the variation of output while neutral technology shocks explain 11 percent for the period 1982:1-2008:3.

In the second set of results (tables 5 and 6), we compute variance decompositions of the forecast error along with 90 percent bootstrapped confidence intervals. As noted by Fisher (2006), the connection between forecast error decompositions and contributions to cycles is not direct. However, the findings reported in tables 5 and 6 roughly confirm the main conclusions from table 3. It is shown that over 12 years, investment specific shocks and R&D shocks explain a fraction of about 45-69 percent and 18-31 percent of the variance of the forecast error of R&D output, respectively. The findings suggest that R&D shocks mainly have a long run effect on the forecast error of the consumption-good sector output as they explain about 35 percent of the forecast error variance 12 years ahead. Overall, the findings show that in the long run, technology shocks jointly explain all the variation of the forecast error of output in both sectors. The estimates also indicate that capital investment-specific shocks are the main contributors of the forecast error variance of hours in both sectors. Note that when R&D is neither treated as investment nor as a separate sector then the joint impact of technology shocks on the forecast error variance reduces. Specifically, over the horizon of 12 years, technology shocks jointly explain up to about 79 percent of the variation of the forecast error of NIPA GDP as opposed to the 100 percent for the two outputs in the full model.

Tables 7 to 10 display variance decompositions when the alternative measure of labor is used. Relative to the benchmark case, the impact of capital investment-specific shocks on outputs increases slightly in both sectors. The impact of R&D technology shocks on the output of the non-R&D sector reduces to about 18 percent while the combined effect of technology shocks on the non-R&D output reduces to 61 percent. The impact of capital

investment-specific shocks on hours becomes smaller in both sectors while the combined effect of technology shocks on hours in the non-R&D sector reduces to significantly to about 35 percent. These results show that even under the extreme assumption of constant individual hours, the significant effects of R&D and capital investment-specific shocks on the output of both sectors remain.

7 Conclusion

In this paper, we examine sources of the excessive volatility in the R&D sector as well as the role and contribution of the sector to aggregate fluctuations. In doing so, we consider the effects of sectoral technology and capital investment-specific shocks in the R&D and non-R&D sectors using a VAR and data from the BEA-NSF satellite account for the period 1959-2007. The shocks are identified by imposing long-run restrictions which are justified by a two-sector general equilibrium model. We show that introducing exogenous changes in sectoral productivities, in addition to investment-specific technical change, into an RBC model motivates three long-run identifying restrictions. First, as in Fisher (2006), the model predicts that the change in capital investment-specific technology is the unique source of the secular trend in the real price of capital investment goods. Second, changes in capital investment-specific technology along with changes in R&D-specific technology are the only sources of permanent shocks to labor productivity in the R&D sector. Third, changes in sectoral technology in the R&D sector and capital investment-specific technology along with changes in sectoral technology in the non-R&D sector are the only sources of permanent shocks to labor productivity in the non-R&D sector. With those restrictions imposed on the

VAR, the three technology shocks are identified.

Our estimates suggest that capital investment specific shocks play the largest role in driving the fluctuations in the R&D sector while the impact of the R&D sector on aggregate fluctuations is substantial given its relative size. Specifically, after controlling for real and nominal factors, capital investment-specific shocks explain 70 percent of fluctuations of R&D investment while technology shocks in the R&D sector explain 30 percent of the variation of output in the non-R&D sector. We find that technology shocks can jointly explain almost all the variation of output in the R&D sector and 78 percent of the variation of output in the rest of the economy. Our findings confirm Ouyang's (2011) proposition that technology shocks are key factors in explaining the procyclicality of R&D.

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Table 1 - Volatilities of growth rates: Annual US data 1959-2007

	real adj. GDP	total employment	R&D investment	R&D employment
Volatility	1.95	1.75	4.01	7.01

Table 2 - Model parameter values

	value		value		value		value
α_1	0.1	λ	0.1	ρ_J	0.65	$\widetilde{e}$	1.018
α_2	0.26	φ_C	1	ρ_A	0.65	δ_R	0.5 or 0.8
κ^*	0.42 or 0.40	φ_R	1	x_Z	1.02		
δ_K	0.1	ρ_Z	0.65	e	1.036		

*Each value of κ corresponds to the parameterization under each value of δ_R.

Table 3 - Contribution of shocks to fluctuations (percent)

	Productivity		Hours		Output	
Shocks\Sectors	R&D	C-sector	R&D	C-sector	R&D	C-sector
Investment	56	38.4	39.1	31.1	69.9	35.4
	(32.7,72.9)	(9.2,65)	(14.3,61.2)	(7.4,54.8)	(46.6,82.1)	(7.9,64)
R&D	12.8	23	4.4	16.7	19.7	30.2
	(5.1,26.1)	(6.6,48.1)	(0.8,15.5)	(5.3,30.3)	(9.7,39.4)	(10.7,52.5)
C-specific	1	12.5	3.2	7.4	1.2	13.7
	(0.2,4.5)	(4,41.6)	(0.6,11.4)	(1.8,17.2)	(0.3,4.1)	(5.5,31.3)
All Technology	74	79	46.1	56.4	92.3	78.5
	(49.4,86.5)	(48.7,91.7)	(21.7,66.8)	(27.6,74.9)	(77,97)	(46.9,91.6)

− The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 4 - Contribution of shocks to fluctuations (percent)
without an R&D sector and shocks

	Productivity	Hours	Output
Investment	39.9	33.3	40.2
	(5.6,71.9)	(5.8,61.4)	(8.9,72)
Neutral	31.1	13	33.3
	(8.9,77.1)	(3.2,31.1)	(14,61)
All Techology	85.8	68.8	90.3
	(43.4,97.5)	(40.9,87.6)	(67,98)

− The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 5 - Forecast error decompositions of the output growth rate (percent)

	R&D Output				C-sector Output with R&D				Output without R&D		
Year	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	All Tech.
1	12.8	44.7	18.3	75.8	9.4	11.4	1.2	22	11.7	13.1	24.8
	(0.2,36.6)	(13.0,58.6)	(0.6,46.7)	(40.7,88.3)	(0.1,41.1)	(0.2,31)	(0,15.6)	(5.1,57.7)	(0.1,50.2)	(0.3,36.6)	(3.5,63.4)
2	1.8	58.3	25.2	85.3	41.5	24.7	14.9	81.1	0.3	22.6	22.9
	(0.0,20.9)	(19.1,72.9)	(2.8,48.5)	(47.6,94.6)	(5.5,65.1)	(0.9,49.0)	(0.3,38.2)	(32.9,92.4)	(0,28.7)	(0.5,49.5)	(3.4,60.3)
3	0	56.9	34.0	91	51.6	18	29	98.6	11.8	35.7	47.4
	(0.0,9)	(23.1,73.1)	(8.7,55.7)	(60.1,97)	(21.4,72.0)	(0.8,42.2)	(5.2,46.8)	(70.3,98.5)	(0.1,44.5)	(2.0,62.4)	(9.9,78.3)
6	0.4	61	36.4	97.8	46.5	16.1	36.5	99.1	53.7	25	78.8
	(0,5.1)	(30.5,76.2)	(16.5,59.2)	(80.6,99.4)	(21.2,73.3)	(0.4,42.0)	(10.2,55.8)	(83.3,99.7)	(6.9,74.4)	(0.9,53.6)	(30.5,89)
12	0	69.3	30.6	100	42.4	22.4	35.2	100	15.6	36.3	51.9
	(0,0.9)	(43.6,81.5)	(17.1,53.7)	(96.2,100)	(19.2,76.2)	(0.6,50.8)	(7.8,55.3)	(94.2,100)	(0.4,73.7)	(0.3,58.4)	(12.1,87.4)

– The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 6 - Forecast error decompositions of hours (percent)

	R&D Hours				C-sector Hours with R&D				Hours without R&D		
Year	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	R&D	All Tech.	Neutral	Invest.	All Tech.
1	1.5	39.1	0.4	41	6.6	0.1	0.9	7.6	5.8	6.5	12.3
	(0,8.7)	(22,51.7)	(0,6)	(26.3,55.5)	(0.1,25.7)	(0,14.7)	(0,16.1)	(2.3,35.8)	(0.1,22.2)	(0.1,23.8)	(2,34.5)
2	10.6	33.1	0.8	44.5	1.8	31.1	4.5	37.4	1.4	23.8	25.2
	(0.2,34.6)	(2.5,59.9)	(0.0,19.4)	(17.8,71.6)	(0,23.3)	(0.5,56.6)	(0,30.8)	(9,72.2)	(0,31.1)	(0.7,50.8)	(4,59)
3	1.8	46.9	0.2	48.9	14.9	28.6	26.8	70.2	12.4	39.0	51.4
	(0,20.9)	(2.7,71.8)	(0,20.9)	(14.3,78.5)	(0.3,32.7)	(0.6,57.5)	(0.8,45.6)	(20.8,86.3)	(0.1,45.2)	(1.6,65)	(9.2,79.9)
6	6.2	49.6	28.5	84.3	15.1	33.6	41.3	90	54.3	24.7	79
	(0,30.4)	(0.8,71.9)	(0.3,46.1)	(18.7,90.6)	(0.4,32.4)	(1.5,61.2)	(7.9,55.6)	(40.5,93.1)	(4.4,75.4)	(0.6,54)	(26.2,89.2)
12	1.2	61.2	4.9	67.2	0.3	61	14.1	75.4	9.5	36.3	45.8
	(0.1,36.2)	(0.7,72.2)	(0.2,47)	(26.6,90.2)	(0,28.4)	(1.5,73.4)	(0.2,44.5)	(27.1,90)	(0.4,74.1)	(0.2,58.5)	(12.3,87.3)

– The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 7 - Contribution of shocks to fluctuations (percent): *alternative measure of labor*

	Productivity		Labor		Output	
Shocks╲Sectors	R&D	C-sector	R&D	C-sector	R&D	C-sector
Investment	59.5	56.5	27.3	17.4	73.5	44.8
	(27.5,77.1)	(20.1,77.3)	(8.2,58.8)	(3.9,46.2)	(46.2,85)	(15.2,66.4)
R&D	20.2	24.3	7.2	11.3	19.5	18.2
	(8.7,41.5)	(9.6,47.6)	(1.7,21.8)	(2.9,26.7)	(9.7,37)	(5.9,34)
C-specific	1	6.4	4.8	6.7	1.3	6.1
	(0.2,4.5)	(2.5,14.3)	(0.8,15.6)	(1.3,18.8)	(0.4,4)	(1.6,13.7)
All Technology	85.2	88.4	46.7	35.3	94.3	61
	(60.7,93.5)	(51.2,96.5)	(22.8,69.5)	(15.8,58.6)	(76.1,97.9)	(24.5,83.6)

– The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 8 - Contribution of shocks to fluctuations (percent) without an R&D sector and shocks: *alternative measure of labor*

	Productivity	Labor	Output
Investment	26.9	11.9	25.5
	(3.2,58.7)	(1,51.2)	(3.4,58.5)
Neutral	57.9	37.8	36.4
	(19.7,87.0)	(7.7,63.7)	(5.1,63.7)
All Techology	93.3	66	71.7
	(51.3,98.5)	(31.4,87.2)	(30.8,90.0)

– The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 9 - Forecast error decompositions of the output growth rate (percent): *alternative measure of labor*

	R&D Output				C-sector Output with R&D				Output without R&D		
Year	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	All Tech.
1	20.7	45.1	12.1	77.9	0.9	9.1	2.9	12.9	1.5	5	6.5
	(1.2,41.6)	(14.8,57.6)	(1,27.5)	(42.5,85.4)	(0,13.6)	(0.1,26.9)	(0,18.5)	(3.7,38.6)	(0,18.4)	(0.1,25.4)	(0.8,32.6)
2	5.8	64.8	16.8	87.5	0.3	12.4	12.6	25.3	63.5	0.1	63.6
	(0.1,24.4)	(26.7,74.5)	(1.8,32.8)	(51.5,92.7)	(0,16.6)	(0.1,42.6)	(0.1,41.4)	(6.3,61.6)	(11.4,85.6)	(0,17.5)	(16.1,88.9)
3	0.8	68.7	25	94.5	9.8	28.2	0.1	38.1	29.9	1.3	31.2
	(0,10.8)	(36.4,77.5)	(7.1,41.6)	(67,96.6)	(0.1,29.5)	(0.8,57.7)	(0,20.3)	(11.2,71.2)	(0.6,64.8)	(0,28.3)	(4.1,71.1)
6	0.2	66	33.4	99.6	24.4	45.2	24.1	93.7	0.1	17	17.1
	(0,3.4)	(38.9,78.4)	(17.6,52.6)	(87,99.6)	(4,42.2)	(9,67.2)	(1.7,41.6)	(43.8,98)	(0.1,56.2)	(0.1,55.5)	(2.6,75)
12	0	69.1	30.8	100	23.9	42.8	33	99.6	13	14.9	27.9
	(0,1.1)	(38.1,83)	(15.5,57.5)	(93.9,100)	(5.7,41.4)	(5.8,68.7)	(7.2,53.5)	(62.3,99.9)	(0.2,72.8)	(0.1,53)	(3.9,82.5)

– The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Table 10 - Forecast error decompositions of hours (percent): other measure of hours: *alternative measure of labor*

	R&D Hours				C-sector Labor with R&D				Labor without R&D		
Year	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	R&D	All Tech.	Neutral	Invest.	All Tech.
1	1.8	39.8	0.5	42.1	14.8	10.6	18.9	44.3	43.7	0.1	43.7
	(0,9.7)	(22.1,52.1)	(0,6)	(26.9,55.9)	(1.6,29.8)	(0.8,24.8)	(3.9,34.4)	(22.9,59.3)	(23.3,59.1)	(0,7)	(25,60.3)
2	19.2	10.5	20.4	50.1	4.3	0.1	24.1	28.5	67.8	0.3	68.1
	(0.8,39.6)	(0.1,40.6)	(0.7,44.5)	(17.4,78.4)	(0,21.9)	(0,18.1)	(1.7,47.8)	(7.1,65.2)	(25.1,85.7)	(0,12.8)	(30.1,88)
3	10.2	9.1	19.8	39.1	1.4	0	18.2	19.6	43.2	0.4	43.6
	(0.2,28.4)	(0.1,40.7)	(0.6,41.4)	(11.3,69.6)	(0,17)	(0,24.4)	(0.3,42.9)	(5,58.5)	(3.3,72.3)	(0,21.9)	(9.1,76.3)
6	2.6	18.9	8.1	29.6	3.9	32.2	3.5	39.6	0.7	13.5	14.2
	(0,25.1)	(0.1,65.9)	(0.1,44.2)	(7.6,79.6)	(0,27.3)	(0.2,63.9)	(0.1,35.5)	(7.4,80.4)	(0.1,54.9)	(0.1,55.3)	(2.7,74.4)
12	14.6	32.1	0.6	47.3	10.2	43	0.8	54	18.1	21.8	39.9
	(0.1,33.5)	(0.2,69.4)	(0.1,46.6)	(13,86.6)	(0.1,32.6)	(0.2,68.5)	(0.1,47.5)	(11.9,86.5)	(0.2,73.4)	(0.1,54.6)	(4.2,82.7)

– The numbers in parenthesis correspond to bootstrapped 90% confidence intervals.

Figure 1 - Share of R&D investment in (adjusted) GDP.
Data source: BEA-NSF satellite account.

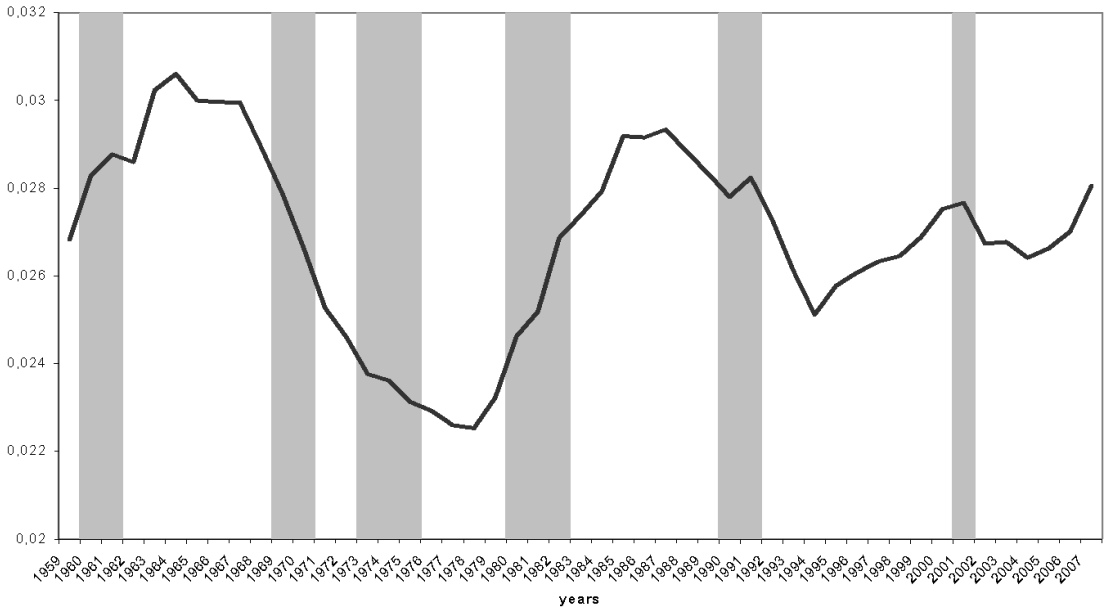

Figure 2 - Theoretical responses to a ***positive*** productivity shock in the R&D sector.

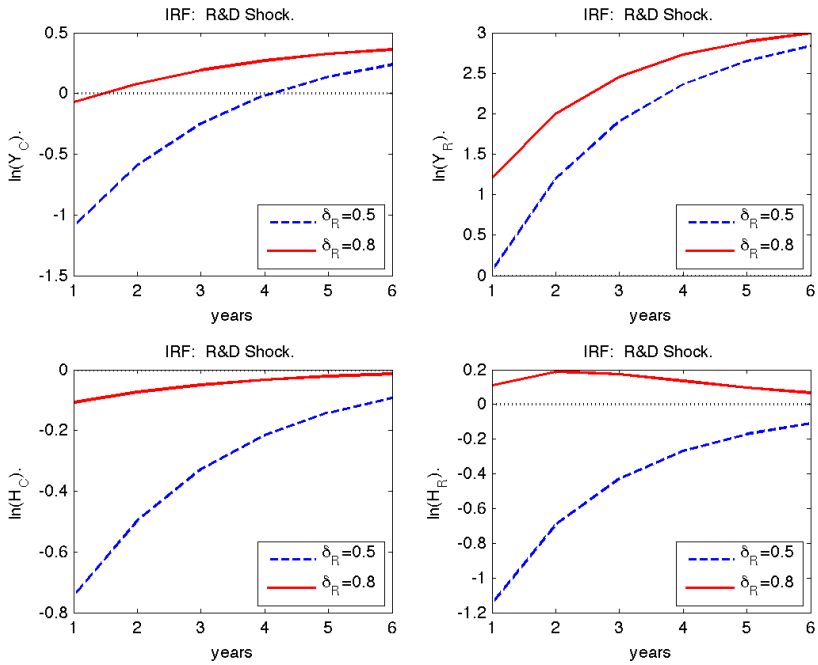

Figure 3 - Theoretical responses to a ***negative*** investment-specific shock.

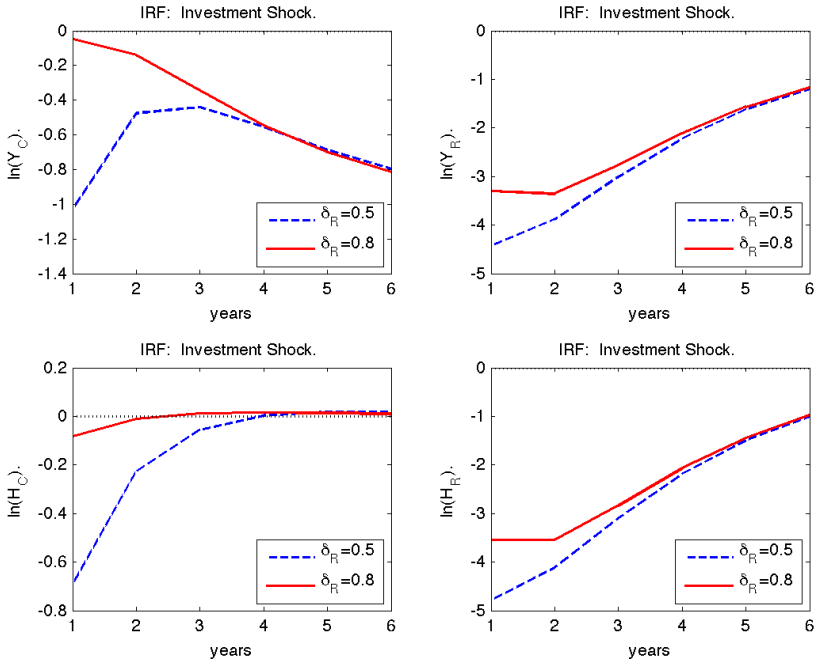

Figure 4 - Theoretical responses to a ***positive*** productivity shock in the consumption-good sector.

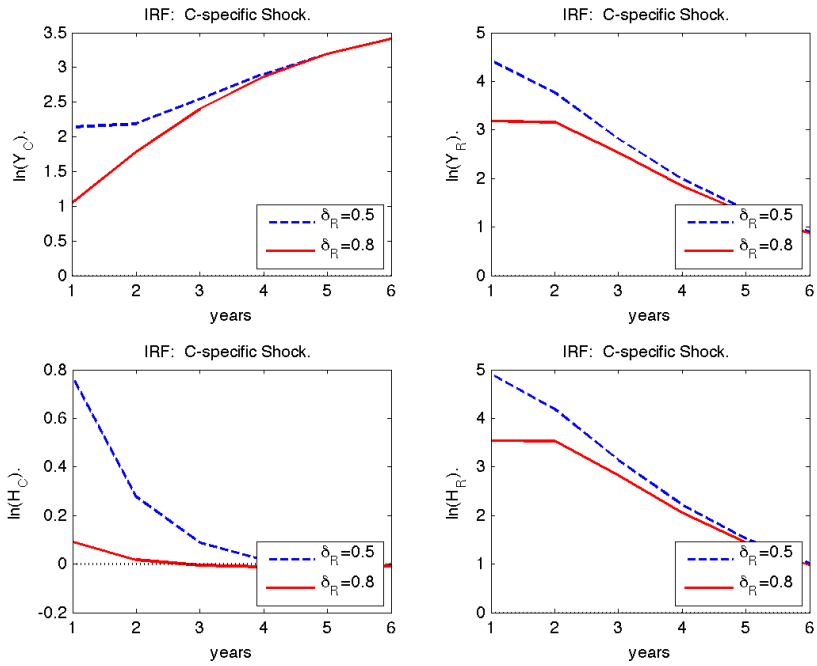

Figure 5 - Response of levels to a ***positive*** productivity shock in the R&D sector.
[- - - , 90% confidence interval]

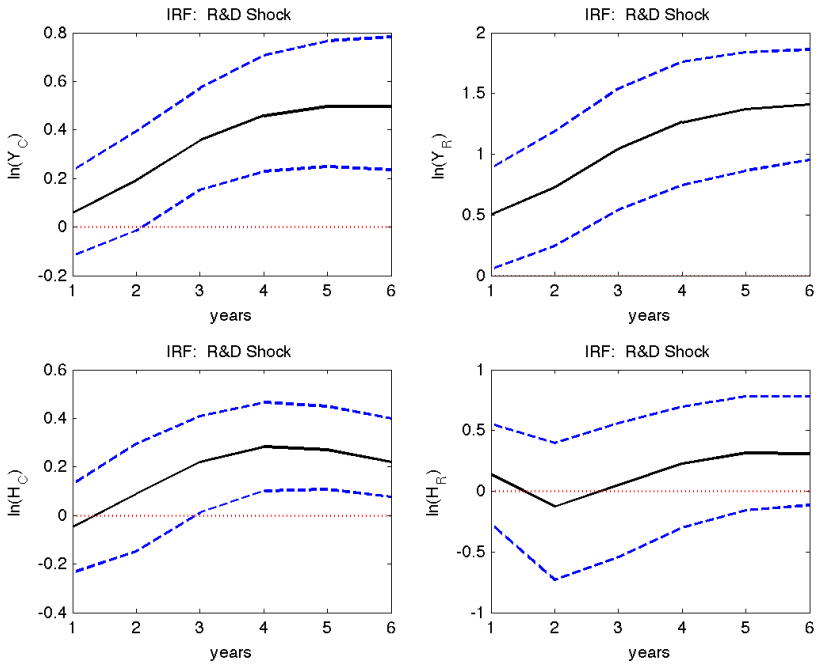

Figure 6 - Response of levels to a ***negative*** investment-specific shock.
[- - - , 90% confidence interval]

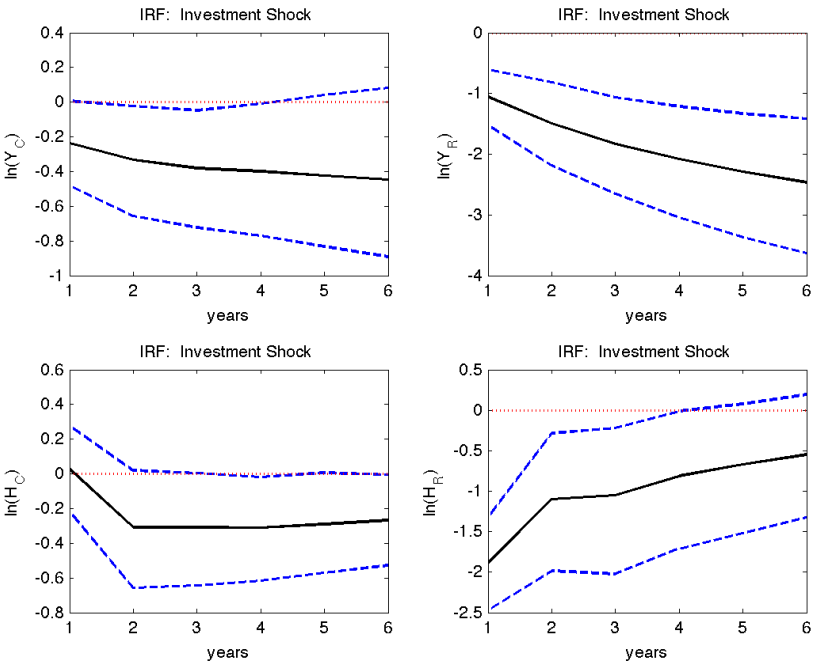

Figure 7 - Response of levels to a ***positive*** productivity shock in the consumption-good sector.
[- - - , 90% confidence interval]

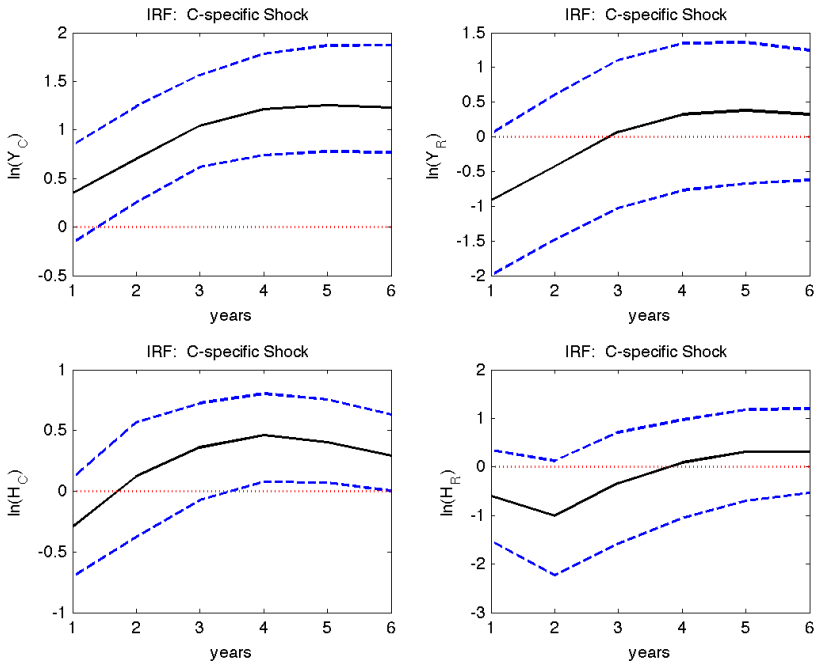
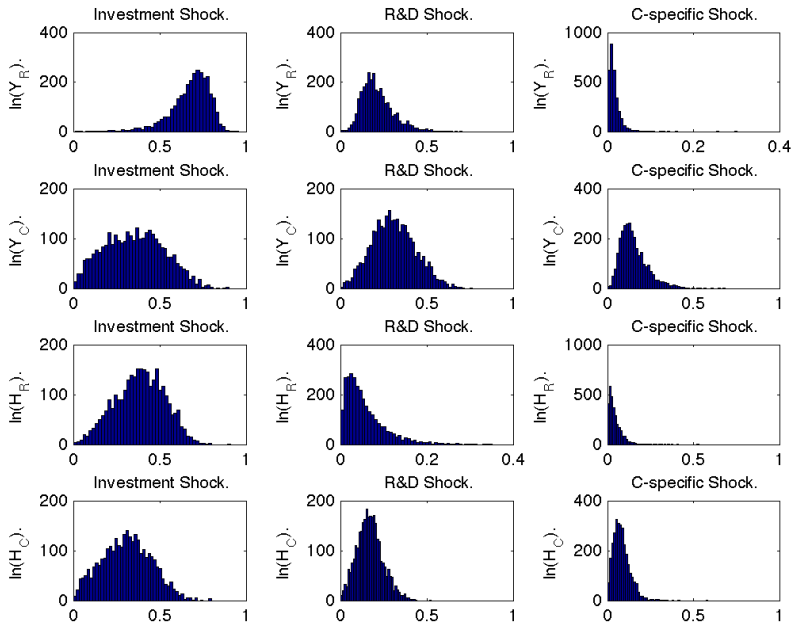
Figure 8 - Distributions of variance decompositions.