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R&D and Aggregate Fluctuations*

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Abstract

Using US data for the period 1959-2007, we identify sectoral productivity shocks and capital investment-specific shocks by employing a Vector Autoregression whose shock structure is disciplined by a 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 (i.e. the output of the non-R&D sector). 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 non-R&D sector.

JEL Classification Codes: C13; C32; C68; E32; O3

Keywords: Cycles; Productivity Shocks; Investment-specific Shocks; R&D; VAR

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1 Introduction

Investment in research and development (henceforth R&D) as well as employment in the R&D sector exhibit substantial fluctuations relative to those of aggregate production and aggregate employment. Moreover, 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 shocks on the R&D sector as well as the contribution of the sector to annual fluctuations. Specifically, we identify sectoral productivity shocks as well as capital investment-specific shocks by employing a Vector Autoregression (VAR) whose shock structure is disciplined by a stochastic general equilibrium model.

Using annual data from the US for the period prior to 2008, 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 analysis suggests that not only sources listed under R&D expenditures contribute to the stock of R&D. While there can be direct additions to the stock of R&D within the R&D sector (identified from 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 cost of the transfer is inversely related to positive R&D shocks. Thus, an improvement in R&D productivity may induce a transfer of sources from the non-R&D sector as investment in the stock of R&D which then augments the production of the non-R&D output. Our calibration suggests that at the steady state such transfers are positive. Consequently, 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 findings confirm Ouyang's (2011) proposition that technology shocks are a cause of the procyclicality of R&D. The evidence suggests that R&D productivity shocks and capital investment-specific shocks not only explain a considerable portion of output variation in the R&D and non-R&D sectors but they also produce responses of the same sign for the outputs of the two sectors.

In their seminal work, Kydland and Prescott (1982) and Long and Plosser (1983) emphasize the role of neutral technology shocks as the main source of business cycle fluctuations. Since then, the *real business cycle* (RBC) approach has been put forward to explain various business cycle phenomena. Greenwood, Hercowitz and Krusell (2000), make a distinction between the aggregate-sector (neutral) technology shocks and capital investment specific shocks that improve the efficiency of newly produced capital.¹ The calibration of their equilibrium model implies that capital investment-specific shocks account for 30 percent of output fluctuations. Fisher (2006), estimates a VAR using long-run restrictions derived from an equilibrium model and finds that neutral and investment-specific shocks combined account for 44-80 percent of output's short-run fluctuations. His findings suggest that capital investment-specific shocks matter more than neutral technology shocks for business cycle fluctuations. The identified technology shocks from the existing RBC literature 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.

¹Investment specific shocks are identified from variations in the real price of capital investment.

Comin and Gertler (2006), stress the significance of R&D in generating medium-run fluctuations. They consider an endogenous growth model where R&D generates new specialized intermediate goods which enhance the production of final goods. They allow for R&D in both the capital good and the consumption good sectors. Their model is impressively successful in capturing the fluctuations of basic macroeconomic variables but does less well in generating the fluctuations of R&D observed in the data.² In our model, we decompose aggregate production into two sectors, the R&D sector and the non-R&D or consumption-good sector. We incorporate the stock of R&D as a distinct input in the production function adopting Griliches' (1979) proposition. Physical capital is mobile between sectors but with a cost. Fluctuations are driven by three types of shocks: two types of sectoral productivity shocks and capital investment-specific shocks. To quantify the impact of R&D on aggregate fluctuations we first estimate a VAR using seven post-war annual time series. Following 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, following Comin and Gertler (2006), we focus our analysis on those frequencies. As shown by Comin and Gertler, information extracted from annual data regarding medium-run fluctuations is virtually the same as that extracted from quarterly data. The plausibility of the empirical impulse responses are assessed by comparing them with the theoretical ones which are generated by the simple equilibrium model.

Previous work by Butler and Pakko (1998), calibrates an endogenous growth model where R&D drives the level of labor augmenting technology which in turn affects the production of

²As noted by the authors, this could be due to measurement errors in the data.

the final good. They assume that business cycles are triggered by a shock specific to R&D and a shock that affects the production of the final good. The specification of technological change is a modified discrete-time version of Jone's (1995) R&D model with duplication externalities, while physical capital is used only in the production of the final good. They demonstrate that R&D shocks improve the persistence of the dynamics of output and productivity. Fátas (2000), also demonstrates the ability of an R&D-based model to generate persistence in the dynamics of output by considering an extension of Shleifer's (1986) model where the flow of ideas is endogenous. Maliar and Maliar (2004), develop an R&D-based model of stochastic endogenous growth where the consumption good, physical capital and increments in R&D stock are produced by the same technology. In their model, a unit of the final good can be costlessly transformed into either a unit of R&D stock, a unit of consumption good or a unit of physical capital. Business cycles are driven by labor augmenting technical progress which depends, to a large extent, on the stock of R&D. Their model is successful in matching several business cycles facts and in accounting for the asymmetry in the shape of business cycles. It predicts however, that R&D moves countercyclically 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.³

Braun and Nakajima (2009) examine the cyclical pattern of R&D using an endogenous growth model which consists of three separate interrelated production sectors: R&D, capital equipment and consumption. As in Butler and Pakko, the production of R&D output is a

³The idea is based on the fact that a firm cannot prevent rival firms from exploiting its innovation as time passes. Since the prospect of a gain during expansions of the economy is greater, there is an incentive for firms to invest more on R&D during those times where profits are high.

function of labor only. The production of equipment is a function of both capital and labor as well as the stock of R&D and business cycles are driven by changes in the level of technologies of the consumption and equipment sectors. Although their model can reproduce most of the observed variation in output, the impact of technology shocks in the equipment sector on output is found to be negligible. The latter stands in contrast to the findings of Greenwood et al. (2000), Fisher (2006) and Altig et al. (2011) who model capital investment-specific shocks as shocks which affect the marginal efficiency of investment. In our model, capital is a factor of production in both the R&D and non-R&D sectors, and only a fraction of the output in the R&D sector is used as increment for the stock of R&D. There is a distinct technology shock which affects productivity in the R&D sector while capital investment-specific shocks are modelled as shocks to the marginal efficiency of investment.

Our analysis designates that capital investment-specific shocks constitute the main source of fluctuations in R&D investment as they account for 70 percent of its variation. The empirical impulse response function indicates that a one percent positive shock in the real price of capital investment induces an immediate one percent decline in R&D investment. The shock induces further declines in R&D investment the following years, reaching 2.5 percent the 6th year from the date of the shock. Our analysis suggests that improvements in productivity in the R&D sector induce a considerably positive impact on the output of the non-R&D sector to the extent that a one percent improvement in productivity in the R&D sector leads to a 4 percent increase in the output of the non-R&D sector 6 years after the occurrence of the shock. The variance decomposition implies that R&D productivity shocks explain 30.2 percent of the variation of output in the non-R&D sector, which exceeds the

impact of 19.7 percent of own sector productivity shocks. 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 92.3 percent and 78.5 percent of the variation of output in the R&D and non-R&D sectors, respectively. Among the three shocks, capital investment-specific shocks cause the biggest impact on hours for both sectors. The findings confirm Ouyang's (2011) claim 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. The combined effect of technology shocks on hours is 46.1 percent for the R&D sector and 56.4 percent for the non-R&D sector.

Excluding the R&D sector as a separate sector in the model and treating R&D solely as an expense according to the NIPA definitions, we show that capital investment-specific shocks and neutral technology shocks explain 40.2 percent and 33.3 percent of the variation of output, respectively. These estimates are not too far from findings of previous studies which use quarterly data (e.g. Fisher, 2006, Altig et al, 2011). The 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. Specifically, the effect of technology shocks on aggregate per capita hours in the simple model is 68.8 percent as opposed to 46.1-56.4 percent in the model with two sectors and R&D investment.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and presents some empirical evidence to underline the significance of R&D on fluctuations. Section 3 lays out the theoretical framework while section 4 presents the stationary equilib-

rium, 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 6 discusses the data. Section 7 presents and analyzes the empirical results from the VAR model. Section 8 concludes.

2 R&D and Aggregate Fluctuations

Indubitably, investment in R&D constitutes the main engine of endogenous growth. There is an enormous literature exploring the links between R&D and economic growth, both empirically and theoretically.⁴ Schumpeter (1939), was probably the first to formalize the idea of innovations as generators of business cycle fluctuations. In his view, innovations which are produced exogenously lead to permanent improvements in the production technology and thereby, promote economic development and stimulate cyclical fluctuations. The empirical literature which relates R&D with fluctuations has been relatively more limited. Lach and Schankerman (1989), find that both R&D activities and capital investment are affected by a common shock which has very persistent effects. They provide evidence that R&D expenditures Granger-cause investment in physical capital after a short lag.⁵ Geroski and Walters (1995), examine innovations in the UK and argue that the procyclical variation in innovation contributes significantly to the procyclical variation in productivity growth. They conclude that although aggregate demand affects innovation activity, it plays only a modest role as opposed to aggregate supply.

⁴Among others, see the work of Lucas (1988), Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), Griliches and Lichtenbergand (1984) and Stokey (1995).

⁵Similar findings are reported by Lach and Rob (1996).

One issue in the literature is that there are no good measures of the contribution of 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. Lach and Schankerman (1989) point out that advancements in science and technology have a direct impact on R&D spending.⁶ We argue that potential shocks identified from fluctuations of R&D expenditures (investment) reflect precisely technological innovations resulting from R&D activities. Griliches (1979), proposes the introduction of the stock of knowledge, approximated by past R&D expenditures, as an input in the production function. This idea is also implemented by Doraszelski and Jaumandreu (2007), who assume a linear accumulation equation for the stock of knowledge in order to estimate production functions and retrieve productivity and its relation with R&D at the firm level.

Throughout our analysis, we use US data on investment in R&D, adjusted GDP and employment for R&D activities. The data on R&D investment and adjusted GDP is provided in the satellite account which is developed jointly by the Bureau of Economic Analysis (BEA) and the National Science Foundation (NSF). Data on domestic employment of R&D-performing companies is provided by NSF.⁷ As shown in figure 1, R&D investment is on average 2.7 percent of nominal GDP and is characterized by the peaks of the mid 1960s,

⁶Work by Rosenberg (1969, 1974), Pakes and Schankerman (1984) and Griliches, Hall and Pakes (1988) also stresses the importance of past technological improvements as factors of current R&D.

⁷In adjusted GDP, contrary to GDP reported in NIPAs, R&D is treated as investment rather than expense. An extensive discussion about the data on R&D investment is presented in section 6.

the mid 1980s and the early 2000s and the trough of the late 1970s. The shadowed bars correspond to the NBER recessions. The figure suggests that there is no clear pattern in the behavior of the share during major recessions.⁸ 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. Evidence against the Schumpeterian view on the cyclicity of R&D is also presented in previous studies (e.g. Fátas, 2000, Barlevy, 2006, Comin and Gertler, 2006). Ouyang (2011), finds that the procyclicality of R&D holds even when one controls for aggregation effects. To do so, she considers an annual panel of (company financed) R&D expenditures and output for 20 US manufacturing industries. She argues that technology shocks is a key factor in explaining the procyclicality of R&D and concludes by noting that future research should investigate this matter, exploring further the response of R&D to technology shocks.

Figure 2 compares the growth rate of real R&D investment with the growth rate of adjusted aggregate real GDP. The figure indicates that occasionally, the growth rates of R&D investment and aggregate output exhibit similar swings but clearly the former is much more volatile than the latter, especially during the 1990's onwards. Figures 3 and 4 plot the growth rate of output against employment, separately for the R&D sector and the rest of the economy (net of R&D).⁹ Figure 3 shows that the growth rate of employment in the R&D sector is substantially more volatile than the growth rate of R&D investment, and

⁸While the share is increasing during the recessions of the 1960's and the 1980's, it is decreasing during the two recessions of the early and mid 1970's and mainly decreasing during the recession of early 2000.

⁹Output and employment in the non-R&D sector are defined as aggregate real adjusted GDP minus real investment in R&D and aggregate employment minus employment of R&D performing companies, respectively.

occasionally exhibits very different swings than the latter. This is not the case in the non-R&D sector (figure 4) where the growth rates of employment and output are highly correlated and exhibit a similar level of volatility. 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. This difference is evident in figure 5 which shows that the correlation between employment in the R&D sector and employment in the non-R&D sector is quite low (correlation coefficient of -0.27), while employment volatility in the former is substantially higher than that in the latter. Table 1 quantifies these observations by reporting volatilities of aggregate employment and aggregate output vs volatilities of R&D employment and R&D investment. In particular, 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.

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

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} :

$$Y_{Ct} \geq C_t + I_{Ct}. \quad (3.1)$$

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

$$Y_{Ct} = A_t (R_t)^{\alpha_1} (K_{Ct})^{\alpha_2} (H_{Ct})^{1-\alpha_1-\alpha_2}, \quad (3.2)$$

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:

$$R_{t+1} = (1 - \delta_R) R_t + D_t, \quad (3.3)$$

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} :

$$Y_{Rt} \geq D_t + I_{Rt}. \quad (3.4)$$

How D_t is determined is discussed below and in the following section. Output, Y_{Rt} , is

produced via the constant-returns to scale production function

$$Y_{Rt} = J_t (K_{Rt})^\lambda (H_{Rt})^{1-\lambda}, \quad (3.5)$$

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 $0 < \lambda < 1$. The stochastic growth rate of J_t is denoted by x_{Jt} .

Only units of investment from the consumption-good sector correspond to units of aggregate investment on one-to-one basis. The units of investment in capital of the R&D sector are converted to units of investment of the consumption-good sector before new capital is produced. Specifically, a time t unit of investment from the R&D sector corresponds to $\kappa \Xi_t$ units of consumption-good investment, where $\kappa > 0$ is scale parameter. In addition, capital is mobile across sectors but not on one-to-one basis. A unit of consumption-good capital corresponds to $1/\kappa \Xi_t$ units of R&D-good capital. It follows that aggregate investment, $I_t > 0$, and aggregate capital stock, $K_t > 0$, are expressed as

$$\begin{aligned} I_t &= I_{Ct} + \kappa \Xi_t I_{Rt}, \\ K_t &= K_{Ct} + \kappa \Xi_t K_{Rt}. \end{aligned} \quad (3.6)$$

The accumulation equation for the stock of capital is given by

$$K_{t+1} = (1 - \delta_K) K_t + Z_t I_t, \quad (3.7)$$

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 (3.1) and

(3.4) hold with equality. Then, using the capital accumulation equation and (3.6) we can write the economy's budget constraint as follows:

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

where \bar{K}_t denotes the additional units of capital at the end of period t ; $\bar{K}_t \equiv K_{t+1} - (1 - \delta_K)K_t$. The budget constraint is similar to that assumed by Acemoglu and Zilibotti (2001) in which 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 the consumption good is the numeraire and \bar{P}_{Kt} and P_{Rt} are the relative prices of capital and R&D, respectively. \bar{P}_{Kt} equals $1/Z_t$ and P_{Rt} equals $\kappa\Xi_t$. Technology Ξ_t is defined as a function of technologies A_t , J_t and Z_t and its exact functional form is derived and discussed 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} ,

$$u(C_t, L_{Ct}, L_{Rt}) = \ln C_t + \varphi_C \ln L_{Ct} + \varphi_R \ln L_{Rt}, \quad (3.8)$$

where $L_{it} = 1 - H_{it}$ for $i = C, R$ and $\varphi_C, \varphi_R > 0$.¹⁰ Then, the Pareto optimal equilibria are

¹⁰The specification of the utility function implies that labor is specific to each sector and it is not mobile across 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. In general, it is difficult to justify flows

obtained from the central planning problem where the representative household maximizes its expected lifetime utility

$$E_0 \sum_{t=1}^{\infty} \beta^t u(C_t, L_{Ct}, L_{Rt}), \quad (3.9)$$

subject to (3.1), (3.2), (3.3), (3.4), (3.5), (3.6) and (3.7). 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 $\hat{x}_t = dx_t/x$ denote the percentage deviation of x_t from its nonstochastic steady state. The processes that drive the exogenous shocks are given by the following vector autoregressive process

$$\hat{x}_{qt} = \rho_q \hat{x}_{qt-1} + \varepsilon_{qt}, \quad \text{for } q = A, Z, J \quad (3.10)$$

where $|\rho_q| < 1$, $\varepsilon_{qt} \sim iid(0, \sigma_q^2)$ with $E(\varepsilon_{pt}, \varepsilon_{qt}) = 0$ for any $q \neq p$.

4 Stationary Equilibrium and Identification

The equilibrium in this economy is described by constraints (3.1) and (3.4), the accumulation equations for the stock of R&D, (3.3), and capital, (3.7), and the following optimality conditions:

$$1 = \beta E_t \left\{ \frac{1}{x_{Ct+1}} \left[\frac{1 - \delta_K}{x_{Zt+1}} + \alpha_2 Z_t \frac{Y_{Ct+1}}{K_{Ct+1}} \right] \right\}, \quad (4.1)$$

$$\frac{C_t}{1 - H_{Ct}} = \frac{1 - \alpha_1 - \alpha_2}{\varphi_C} \frac{Y_{Ct}}{H_{Ct}}, \quad (4.2)$$

from and especially to the highly specialized R&D sector. Even if we allow perfect labor mobility across the two sectors by assuming a representative agent allocating her time between working in the consumption-good sector, working in the R&D sector and leisure, the results of the next section will still hold. In either case, the VAR analysis that follows does not depend on whether labor is mobile or immobile across sectors.

$$\frac{C_t}{1 - H_{Rt}} = \frac{1 - \lambda}{\varphi_R} \frac{Y_{Rt}}{H_{Rt}} \kappa \Xi_t, \quad (4.3)$$

$$\alpha_2 \frac{Y_{Ct}}{K_{Ct}} = \lambda \frac{Y_{Rt}}{K_{Rt}}, \quad (4.4)$$

$$1 = \beta E_t \frac{1}{x_{Ct+1}} \left\{ \frac{\alpha_1}{\kappa \Xi_t} \frac{Y_{Ct+1}}{R_{t+1}} + (1 - \delta_R) x_{\Xi t+1} \right\}, \quad (4.5)$$

where $x_{Ct} = C_t/C_{t-1}$ and $x_{\Xi t} = \Xi_t/\Xi_{t-1}$. Condition (4.1), is the optimal condition for next period capital stock. Conditions (4.2) and (4.3) correspond to the optimal choice for work effort in the consumption-good and the R&D sector, respectively. Condition (4.4) determines the optimal allocation of capital across sectors while condition (4.5) determines the optimal choice for next period stock of R&D.

We identify the three technology shocks by considering their effects over the long-run. As we have shown in the previous section, the real price of investment is equal to the inverse of investment-specific technological progress.¹¹ As in 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. 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 due to the fact that in the long-run those innovations reduce both the nominal price of capital investment and the aggregate nominal price (numeraire), leaving the long-run price ratio unaffected.¹² This implication follows from the assumed segregation of the R&D and

¹¹See also Hornstein and Krusell (1996), Greenwood, Hercowitz and Krusell (2000), Cummins and Violante (2002) and Fisher (2006).

¹²In the empirical part of section 5, R&D-based innovations affect the real price of capital investment only in the short-run.

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.

The identification of shocks specific to the R&D sector follows from the assumption that shocks specific to the consumption-good sector do not affect the R&D sector in the long-run. The latter enables us to scale the trending variables, eliminating steady state growth. The optimality conditions can then be expressed in terms of stationary variables. Consequently, we establish the following proposition.

Proposition: *The resource constraints (3.1) and (3.4), the accumulation equations for the stock of R&D, (3.3), and capital, (3.7), and the optimality conditions (4.1)-(4.5), 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*

$$y_{Ct} = Y_{Ct}/\tilde{X}_t, y_{Rt} = Y_{Rt}/X_t, k_{Ct} = K_{Ct}/\tilde{X}_t Z_t, k_{Rt} = K_{Rt}/X_t Z_t, k_t = K_t/\tilde{X}_t Z_t,$$

$$i_{Ct} = I_{Ct}/\tilde{X}_t, i_{Rt} = I_{Rt}/X_t, c_t = C_t/\tilde{X}_t, d_t = D_t/X_t \text{ and } r_t = R_t/X_t$$

$$\text{with } X_t = (J_t)^{\frac{1}{1-\lambda}} (Z_t)^{\frac{\lambda}{1-\lambda}}, \tilde{X}_t = (A_t)^{\frac{1}{1-\alpha_2}} (X_t)^{\frac{\alpha_1}{1-\alpha_2}} (Z_t)^{\frac{\alpha_2}{1-\alpha_2}} \text{ and } \Xi_t = \tilde{X}_t/X_t.$$

As we show further below, the proposition implies intuitive relationships between the relative price of R&D and the stochastic processes A_t and J_t . The proposition also implies that at the steady state the non-stationary variables Y_{Rt} , K_{Rt} , I_{Rt} , D_t and R_t are affected only by J_t and Z_t . Let the growth rates of X_t and \tilde{X}_t be denoted by $e_t = (x_{Jt})^{\frac{1}{1-\lambda}} (x_{Zt})^{\frac{\lambda}{1-\lambda}}$ and $\tilde{e}_t = (x_{At})^{\frac{1}{1-\alpha_2}} (e_t)^{\frac{\alpha_1}{1-\alpha_2}} (x_{Zt})^{\frac{\alpha_2}{1-\alpha_2}}$, 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 $\tilde{e}_t - 1$, variable K_{Rt} grows at the rate $e_t x_{Zt} - 1$ and variables K_{Ct} and K_t grow at the rate $\tilde{e}_t x_{Zt} - 1$.

The stochastic processes have an effect on the relative price of R&D which in turn affects the distribution of resources between the consumption-good sector and the R&D sector. The relative (real) price of R&D can be written as $\kappa \Xi_t = \kappa (A_t)^{\tau_{\Xi,A}} (J_t)^{\tau_{\Xi,J}} (Z_t)^{\tau_{\Xi,Z}}$, 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 :

$$\tau_{\Xi,A} = \frac{1}{1 - \alpha_2}, \quad \tau_{\Xi,J} = -\frac{(1 - \alpha_1 - \alpha_2)}{(1 - \lambda)(1 - \alpha_2)}, \quad \tau_{\Xi,Z} = \frac{\alpha_2 - \lambda(1 - \alpha_1)}{(1 - \lambda)(1 - \alpha_2)}.$$

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 $\lambda(1 - \alpha_1)$.¹³

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

¹³The higher the share of capital in R&D-sector output the more beneficial for the R&D sector are improvements in investment-specific technological progress. Likewise, the higher the share of capital in consumption-sector output the more beneficial for the consumption-good sector are improvements in investment-specific technological progress.

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 latter coupled with anticipation of future gains from R&D motivates the transfer of sources towards the R&D sector. This means that part of I_{Ct} can be invested in the stock of R&D (i.e. $I_{Ct} > I_t$). Among others, the latter can be thought of as sources increasing human capital. Thus, a positive R&D shock may induce a flow of sources 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 sources 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.

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.¹⁴ In addition, we set the 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 $(\tilde{e} - 1 =)$ 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.¹⁵ The discount factor, β , is chosen to be 0.95 which is a value typically 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 chosen 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.¹⁶ The persistency 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. Since the R&D sector is labor intensive, we set the share of labor, $(1 - \lambda)$, in the output of the sector to 0.9.¹⁷ As noted by Hall (2007), and previously by Griliches (2000), the measurement of depreciation of R&D assets is the central

¹⁴Note that real aggregate output can be written as $Y_t = Y_{Ct} + \kappa \Xi_t Y_{Rt}$ which can be expressed as $\kappa(y_{Rt}/y_{Ct}) = (Y_t/Y_{Ct}) - 1$. The latter is introduced as an additional equation in the system of steady state equations so that the set of parameter values are consistent with a steady state ratio of Y/Y_C equal to 1.03.

¹⁵Those 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.

¹⁶The 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.

¹⁷Most 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.

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.¹⁸ In this paper, we 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 by the steady state equations. It is worth noting that the calibration implies that at the steady state there is a positive transfer of sources 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 6, 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

¹⁸According 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 discussion see Hall (2007).

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 today toward consumption in the future, they also tend to decrease work effort as they feel wealthier (wealth effect). Figure 6 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 7, displays the responses of output and hours to a negative capital investment-specific shock. The deterioration of investment-specific technology always induce negative responses in both sectors. In this case, the intertemporal 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 8, 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 intertemporal substitution effects.

5 VAR Estimation

We embed our identifying assumptions and the structure of our economic model as restrictions on the parameters of the following VAR:

$$\mathbf{C}\mathbf{y}_t = \mathbf{\Psi}_1\mathbf{y}_{t-1} + \mathbf{\Psi}_2\mathbf{y}_{t-2} + \cdots + \mathbf{\Psi}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t, \quad (5.1)$$

where \mathbf{y}_t is a vector of time t variables, $\boldsymbol{\varepsilon}_t$ is a vector of time t structural shocks, with a diagonal variance-covariance matrix $E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') = \boldsymbol{\Sigma}$, and \mathbf{C} is a matrix that contains the contemporaneous relations of the variables in \mathbf{y}_t (with ones in the diagonal). 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.

The assumption that capital investment-specific technological change is the unique source of the secular trend in the real price of capital investment goods is commonly used by previous studies (Fisher, 2006, Altig et al., 2011). The presence of capital as a factor of production in both sectors justifies the fact that capital investment-specific shocks affect labor productivities in both sectors in the long-run. The rest of the assumptions follow from the fact that production in the non-R&D sector is explicitly augmented by the stock of R&D while the reverse does not hold. The latter is due to the fact that the level of output in the non-R&D sector does not have a direct impact on R&D activities. Note that these arguments hold only in the long-run; in the short and medium run productivity shocks in the non-R&D sector affect production in the R&D sector.

We define \mathbf{y}_t as $[\Delta \ln (P_{Kt}/P_{GDPt}), \Delta \ln (Y_{Rt}/H_{Rt}), \Delta \ln (Y_{Ct}/H_{Ct}), \ln H_{Rt}, \ln H_{Ct}, \mathbf{\Lambda}_t]'$ where $\Delta \equiv 1 - L$ with L being the lag operator, P_{Kt} is the nominal price of capital investment and P_{GDPt} is the GDP price index. Following Fisher (2006), vector $\mathbf{\Lambda}_t$, which consists of the inflation rate and the nominal interest rate, is included in order to capture potential effects of monetary policy. Let $\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}_{1t}, \boldsymbol{\varepsilon}_{2t}]'$ where $\boldsymbol{\varepsilon}_{1t} = [\varepsilon_{Zt}, \varepsilon_{Jt}, \varepsilon_{At}]'$ and $\boldsymbol{\varepsilon}_{2t} = [\varepsilon_{Rt}, \varepsilon_{Ct}, \varepsilon_{It}, \varepsilon_{INt}]'$. Following Fisher (2006), each regression row of (5.1) is estimated sequentially. The first equation of (5.1) is

$$\begin{aligned} \Delta \ln \left(\frac{P_K}{P_{GDP}} \right)_t &= \boldsymbol{\Phi}_P + \boldsymbol{\Phi}_{PP}(L) \Delta \ln \left(\frac{P_K}{P_{GDP}} \right)_{t-1} + \boldsymbol{\Phi}_{PR}(L) \Delta \ln \left(\frac{Y_R}{H_R} \right)_t + \\ &\boldsymbol{\Phi}_{PRH} \ln (H_{Rt}) + \boldsymbol{\Phi}_{PCH} \ln (H_{Ct}) + \boldsymbol{\Phi}_{PC}(L) \Delta \ln \left(\frac{Y_C}{H_C} \right)_t + \boldsymbol{\Phi}_{P\Lambda}(L) \mathbf{\Lambda}_t + \varepsilon_{Zt}. \end{aligned} \quad (5.2)$$

As indicated by Fisher (2006), restriction 1 is equivalent to imposing a unit root in each of the lag polynomials associated with $\Delta \ln (Y_{Rt}/H_{Rt})$, $\Delta \ln (Y_{Ct}/H_{Ct})$, $\ln (H_{Rt})$, $\ln (H_{Ct})$ and $\mathbf{\Lambda}_t$. Doing so, the coefficients of (5.2) become $\boldsymbol{\Phi}_{Pi}(L) = \tilde{\boldsymbol{\Phi}}_{Pi}(L)(1 - L)$ and the regression is rewritten as

$$\begin{aligned} \Delta \ln \left(\frac{P_K}{P_{GDP}} \right)_t &= \boldsymbol{\Phi}_P + \boldsymbol{\Phi}_{PP}(L) \Delta \ln \left(\frac{P_K}{P_{GDP}} \right)_{t-1} + \tilde{\boldsymbol{\Phi}}_{PR}(L) \Delta^2 \ln \left(\frac{Y_R}{H_R} \right)_t + \\ &\tilde{\boldsymbol{\Phi}}_{PRH} \Delta \ln (H_{Rt}) + \tilde{\boldsymbol{\Phi}}_{PCH} \Delta \ln (H_{Ct}) + \tilde{\boldsymbol{\Phi}}_{PC}(L) \Delta^2 \ln \left(\frac{Y_C}{H_C} \right)_t + \\ &\tilde{\boldsymbol{\Phi}}_{P\Lambda}(L) \Delta \mathbf{\Lambda}_t + \varepsilon_{Zt}. \end{aligned} \quad (5.3)$$

Since investment-specific shocks are not orthogonal to the variables on the right hand side, ordinary least squares will give inconsistent estimates. According to our economic model the exogenous shock ε_{Zt} is uncorrelated with variables at $t - 1$. Consequently, N lags of variables $\Delta^2 \ln (Y_{Rt}/H_{Rt})$, $\Delta^2 \ln (Y_{Ct}/H_{Ct})$, $\Delta \ln (H_{Rt})$, $\Delta \ln (H_{Ct})$ and $\Delta \mathbf{\Lambda}_t$ are used as instruments.

According to restriction 2, only R&D shocks and investment specific shocks have an impact on labor productivity in the R&D sector in the long-run. This amounts to imposing unit roots on $\Delta \ln(Y_{Ct}/H_{Ct})$, $\ln(H_{Rt})$, $\ln(H_{Ct})$ and Λ_t and thereby the second equation of (5.1) reduces to

$$\begin{aligned} \Delta \ln \left(\frac{Y_R}{H_R} \right)_t &= \Phi_{YR} + \Phi_{RR}(L) \Delta \ln \left(\frac{Y_R}{H_R} \right)_{t-1} + \Phi_{RP}(L) \Delta \ln \left(\frac{P_K}{P_{GDP}} \right)_{t-1} + \\ &\quad \tilde{\Phi}_{RRH} \Delta \ln(H_{Rt}) + \tilde{\Phi}_{RCH} \Delta \ln(H_{Ct}) + \tilde{\Phi}_{RC}(L) \Delta^2 \ln \left(\frac{Y_C}{H_C} \right)_t + \\ &\quad \tilde{\Phi}_{RA}(L) \Delta \Lambda_t + \theta_R \hat{\varepsilon}_{Zt} + \varepsilon_{Jt}, \end{aligned} \quad (5.4)$$

where $\hat{\varepsilon}_{Zt}$ denotes the estimated residuals of (5.3). We include the estimate of ε_{Zt} as an instrument in the regression to ensure that $\hat{\varepsilon}_{Jt}$ will be orthogonal to $\hat{\varepsilon}_{Zt}$. As in the previous case, to estimate (5.4), we use N lags of variables $\Delta^2 \ln(Y_{Ct}/H_{Ct})$, $\Delta \ln(H_{Rt})$, $\Delta \ln(H_{Ct})$ and $\Delta \Lambda_t$ as instruments.

Having estimates for $\{\varepsilon_{Zt}\}$ and $\{\varepsilon_{Jt}\}$ what is left is to estimate technology shocks specific to the non-R&D sector, $\{\varepsilon_{At}\}$. Restriction 3 states that only shocks in ε_{1t} affect productivity in the consumption good sector in the long-run. Imposing the appropriate unit roots on the independent variables, the third equation of (5.1) reduces to

$$\begin{aligned} \Delta \ln \left(\frac{Y_C}{H_C} \right)_t &= \Phi_{YC} + \Phi_{CC}(L) \Delta \ln \left(\frac{Y_C}{H_C} \right)_{t-1} + \Phi_{CP}(L) \Delta \ln \left(\frac{P_K}{P_{GDP}} \right)_{t-1} + \\ &\quad \tilde{\Phi}_{CRH} \Delta \ln(H_{Rt}) + \tilde{\Phi}_{CCH} \Delta \ln(H_{Ct}) + \Phi_{CR}(L) \Delta \ln \left(\frac{Y_R}{H_R} \right)_{t-1} + \\ &\quad \tilde{\Phi}_{CA}(L) \Delta \ln(\Lambda_t) + \theta_{CZ} \hat{\varepsilon}_{Zt} + \theta_{CJ} \hat{\varepsilon}_{Jt} + \varepsilon_{At}, \end{aligned} \quad (5.5)$$

where $\hat{\varepsilon}_{Zt}$ and $\hat{\varepsilon}_{Jt}$ are estimates of the shocks from the previous regressions. Equation (5.5) is estimated using N lags of variables $\Delta \ln(H_{Rt})$, $\Delta \ln(H_{Ct})$ and $\Delta \Lambda_t$ as instruments.

Note that system (5.1) can be written as

$$\begin{pmatrix} \mathbf{C}^{11} & \mathbf{C}^{12} \\ 3x3 & 3x4 \end{pmatrix} \begin{pmatrix} \mathbf{y}_{1t} \\ 3x1 \end{pmatrix} = \begin{pmatrix} \Psi^{11}(L) & \Psi^{12}(L) \\ 3x3 & 3x4 \end{pmatrix} \begin{pmatrix} \mathbf{y}_{1t-1} \\ 3x1 \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon}_{1t} \\ 3x1 \end{pmatrix}, \quad (5.6)$$

$$\begin{pmatrix} \mathbf{C}^{21} & \mathbf{C}^{22} \\ 4x3 & 4x4 \end{pmatrix} \begin{pmatrix} \mathbf{y}_{2t} \\ 4x1 \end{pmatrix} = \begin{pmatrix} \Psi^{21}(L) & \Psi^{22}(L) \\ 4x3 & 4x4 \end{pmatrix} \begin{pmatrix} \mathbf{y}_{2t-1} \\ 4x1 \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon}_{2t} \\ 4x1 \end{pmatrix},$$

where $\mathbf{y}_{1t} = [\Delta \ln(P_{Kt}/P_{GDPt}), \Delta \ln(Y_{Rt}/H_{Rt}), \Delta \ln(Y_{Ct}/H_{Ct})]'$ and $\mathbf{y}_{2t} = [\ln H_{Rt}, \ln H_{Ct}, \boldsymbol{\Lambda}_t]'$. Notice that the coefficients \mathbf{C}^{11} , \mathbf{C}^{12} , $\Psi^{11}(L)$ and $\Psi^{12}(L)$ are derived by unravelling the estimates from (5.3), (5.4) and (5.5). Therefore, the first three equations of the system are exactly identified. On the contrary, the last four equations of (5.6) cannot be identified because the structural error $\boldsymbol{\varepsilon}_{2t}$ cannot be identified separately from the reduce-form error $(\mathbf{C}^{22})^{-1} \boldsymbol{\varepsilon}_{2t}$. Nevertheless, the shocks in $\boldsymbol{\varepsilon}_{2t}$ can be identified up to a particular transformation. It can be shown that there is a family of observational equivalent parameterizations of the structural form where the responses of \mathbf{y}_{2t} to the shocks in $\boldsymbol{\varepsilon}_{1t}$ are invariant. To see this, let Θ be the following orthonormal matrix:

$$\Theta = \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ 3x3 & 3x4 \\ \mathbf{0} & \boldsymbol{\theta} \\ 4x3 & 4x4 \end{pmatrix},$$

where \mathbf{I} denotes the identity matrix and $\boldsymbol{\theta}$ is an orthonormal matrix. Premultiplying both sides of (5.6) by Θ , the last four equations can be written in reduced form as

$$\mathbf{y}_{2t} = (\mathbf{C}^{22})^{-1} \Psi^{21}(L) \mathbf{y}_{1t-1} + (\mathbf{C}^{22})^{-1} \Psi^{22}(L) \mathbf{y}_{2t-1} - (\mathbf{C}^{22})^{-1} \mathbf{C}^{21} \mathbf{y}_{1t} + \boldsymbol{\Gamma} \boldsymbol{\varepsilon}_{2t}, \quad (5.7)$$

where $\mathbf{\Gamma} = (\boldsymbol{\theta}\mathbf{C}^{22})^{-1}$ and $\boldsymbol{\epsilon}_{2t} = \boldsymbol{\theta}\boldsymbol{\epsilon}_{2t}$. Let $\widehat{\mathbf{C}}^{22}$ be an estimate of \mathbf{C}^{22} and $\widehat{\boldsymbol{\epsilon}}_{2t}$ be the corresponding fitted disturbances. An alternative estimate of \mathbf{C}^{22} is $\widetilde{\mathbf{C}}^{22} = \boldsymbol{\theta}\widehat{\mathbf{C}}^{22}$ with corresponding disturbances $\widetilde{\boldsymbol{\epsilon}}_{2t} = \boldsymbol{\theta}\widehat{\boldsymbol{\epsilon}}_{2t}$. The estimates $\widehat{\mathbf{C}}^{22}$ and $\widetilde{\mathbf{C}}^{22}$ fit the data equally well. If $(\widehat{\mathbf{C}}^{22})^{-1}$ is lower triangular then the last two equations in (5.6) can be estimated sequentially using the residuals of the previously estimated equations. Suppose that $(\widehat{\mathbf{C}}^{22})^{-1}$ is not lower triangular. Since $\widehat{\mathbf{C}}^{22}$ is nonsingular, there exist an orthonormal matrix $\boldsymbol{\theta}$ and a lower triangular matrix \mathbf{R} such that $\widehat{\mathbf{C}}^{22} = \boldsymbol{\theta}'\mathbf{R}$. It follows that $\boldsymbol{\theta}\widehat{\mathbf{C}}^{22} = \mathbf{R}$ is lower triangular, which implies that $\widehat{\mathbf{\Gamma}} = (\widehat{\mathbf{C}}^{22})^{-1}\boldsymbol{\theta}'$ is lower triangular. Consequently, the fourth equation in (5.6) is estimated using $\widehat{\boldsymbol{\epsilon}}_{Zt}$, $\widehat{\boldsymbol{\epsilon}}_{Jt}$ and $\widehat{\boldsymbol{\epsilon}}_{At}$ as regressors to ensure orthogonality with $\widehat{\boldsymbol{\epsilon}}_{Rt}$ and the fifth equation is estimated using $\widehat{\boldsymbol{\epsilon}}_{Zt}$, $\widehat{\boldsymbol{\epsilon}}_{Jt}$, $\widehat{\boldsymbol{\epsilon}}_{At}$ and $\widehat{\boldsymbol{\epsilon}}_{Rt}$ as regressors to ensure orthogonality with $\widehat{\boldsymbol{\epsilon}}_{Ct}$. The sixth and the seventh equations are estimated in a similar way. All four equations are estimated by IV, using N lags of \mathbf{y}_t as instruments.

6 Data

In this section we provide extensive analysis on the measurement of R&D investment as well as description of the other variables (and their components) used in the empirical analysis.

6.1 Measuring R&D output

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 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.¹⁹ Although those expenditures are included in GDP, they are not treated as investment which means that 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.²⁰ The nominal value of R&D is the sum of the costs of the R&D activity of both private and government organizations. Private organizations consist of businesses such as private universities and colleges, private hospitals, charitable foundations, other nonprofit institutions serving households and most Federally Funded Research and Development Centers (FFRDC). Government organizations consist of the Federal Government, state and local governments (excluding uni-

¹⁹Expenditures on R&D by government and nonprofit institutions are included in consumption expenditures; Federal purchases of R&D, expenditures on in-house R&D performed by the Federal Government and state and local purchases of R&D are included in government consumption; Spending on R&D by foundations and non-profit institutions serving households are included in personal consumption expenditures; R&D services are also included in exports and imports while the cost of patents for the use of R&D are included in royalties and licencing fees. For more information refer to Mataloni and Moylan (2007).

²⁰BEA plans to formally incorporate R&D spending as investment into its core accounts around 2013.

versities and colleges), public universities and colleges, and FFRDCs administered by state and local governments (primarily public universities and colleges). The BEA prepares all estimates of current-dollar R&D investment by first compiling data available from the various NSF surveys and then adjusting these data to be statistically and conceptually consistent with BEA definitions in the NIPA tables.

Real R&D investment is derived by deflating detailed current-dollar expenditures by appropriate price indexes. Two price indexes are constructed and utilized in the satellite account: an input price index and an aggregate output-based price index. The input price index is based on an aggregation of detailed price indexes for the inputs used to create R&D output. As noted by Lee and Schmidt (2010), this index is a good measure of the impact of inflation on R&D inputs but less appropriate in measuring R&D output because it does not account for productivity growth; it makes the assumption that real output grows at the same rate as real inputs. On the other hand, the aggregate output-based index, indirectly reflects the movement of R&D output prices. In particular, it is a weighted average of the output prices of other products produced by 14 R&D-intensive industries with weights corresponding to each industry's share of annual business R&D investment. There are two issues related to this index. First, it is influenced by factors that are unrelated to R&D which affect prices of other products produced by the same industries. Second, before 1987, it was constructed based on only the top five industry R&D performers because detailed industry investment measures were unavailable.²¹ Despite those issues, the output-based price index is the best price measure available capturing productivity growth in R&D-intensive industries and thus,

²¹For more details about the index refer to Okubo et al. (2006) and Lee and Schmidt (2010).

it is used throughout our analysis to deflate nominal R&D investment.

6.2 Other Variables used in the Analysis

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. The former is obtained from the BEA-NSF R&D satellite account while the latter from the NSF annual survey.²² Our sample excludes the turbulent period after 2007.

Total hours worked in each sector are defined as the number of employed multiplied by average hours worked during the reference year. While data on aggregate average hours worked is available, data on individual hours that correspond to workers employed in the R&D sectors is not reported. In our benchmark specification, H_{Rt} is computed as employment in the R&D sector multiplied by per capita hours in the nonfarm business sector divided by a population measure that refers to population over 16 years old (US Census Bureau).²³ To compute hours in the consumption-good sector, we first compute employment in the sector as employment in the nonfarm business sector minus employment in the R&D sector. Then, H_{Ct} is computed as employment in the sector multiplied by per capita hours in the

²²The NSF reports data on domestic employment by R&D performing companies which does not include universities and government. Although there are various statistics for employment from NSF surveys, there are difficulties in constructing an aggregate measure of R&D employment series. First, there are no complete data for all years of our sample and second, it is unclear which of the participants in the surveys are actually involved in performing R&D activities. Given those issues and since R&D investment by universities and government constitutes, on average, only 20 percent of total R&D investment we approximate aggregate employment for R&D by the domestic employment of R&D performing companies.

²³Altig, Christiano, Eichenbaum and Linde (2011) compute their measure of aggregate per capita hours in the same way. Nonfarm business hours and employment are published by the Bureau of Labor Statistics.

nonfarm business sector, divided by the population measure. Consequently, the difference in the variation of H_{Rt} over H_{Ct} is due to variation in employment.²⁴ Figure 9 displays the annual growth rate of total hours versus the annual growth rate of total employment. As the figure shows, the two series 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.²⁵

As in Fisher (2006), the price index of capital investment, P_K , corresponds to the price of total investment and is constructed with the equipment deflator and the NIPA (National Income and Product Accounts) deflators for residential and nonresidential 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

²⁴Previous 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)), especially at annual frequencies.

²⁵The 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.

measure.²⁶ 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 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. Galí, 1999, 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 first-differences produces confidence intervals for hours and other variables that diverge to infinity as the horizon increases.

7 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

²⁶Aggregate 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.

dynamics in the data.²⁷ This corresponds to one lag at annual frequencies. The one year lag is also a preferable choice given the short 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.

7.1 Impulse Response Functions

Figure 10 displays impulse response functions to a one standard deviation positive productivity shock (ε_{Jt}) in the R&D sector. The two dashed lines correspond to a 90 percent confidence interval computed by non-parametric bootstrap. The size of the confidence intervals are not very different from confidence intervals of similar studies with quarterly data (e.g. the 95 percent confidence intervals for neutral shocks in Altig et al., 2011). When the shock occurs, the output of the R&D sector increases instantly by 0.5 percent, and continues to increase till the peak of 1.4 percent in the sixth year from the date of the occurrence of the shock. The response of output in the consumption-good sector becomes significantly positive and increasing after the second year following the occurrence of the shock, reaching a peak of 0.5 percent in the sixth year following the occurrence of the shock.²⁸ Hours in the R&D sector exhibit a small increase in response to the sectoral productivity shock, followed by a

²⁷For instance, see Christiano, Eichenbaum and Evans (2005), Altig, Christiano, Eichenbaum and Linde (2005) and Fisher (2006).

²⁸Notice 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.

decrease and eventually by an increase. The sign of the response however is not statistically significant, at least for the first four periods. Hours in the consumption-good sector exhibit a gradual increase which is clearly statistically significant, in terms of sign, after the third period following the occurrence of the shock.

Figure 11 displays impulse response functions to a one standard deviation positive shock in the real price of capital investment. The latter is equivalent to a one standard deviation negative shock in investment-specific technology Z_t (i.e. a negative, ε_{Zt} , shock that decreases Z_t). The negative (positive) shock in Z_t causes a statistically significant prolonged decrease (increase) in output in the R&D sector. R&D output decreases instantly by 1 percent and continues to decrease with a peak decline of 2.5 percent over the period displayed. The positive shock in the real price of investment causes a statistically significant decline in hours in the R&D sector. Specifically, a 1 percent increase in the real price of investment causes a sharp decline in work effort of almost 2 percent. The response of hours continues to remain below its initial level over the period displayed but diminishes gradually. Those responses indicate the big impact of changes in investment-specific technology on fluctuations of R&D activity. Output in the consumption-good sector responds negatively to a negative investment-specific shock with an initial response of 0.2 percent which is marginally statistically significant. Hours in the consumption-good sector do not respond instantly to the shock but decline gradually reaching a trough of 0.3 percent. The negative response of hours is only marginally statistically significant throughout the period displayed. Note that the decrease in R&D output and hours in response to the shock is much larger which suggests that the R&D sector is relatively more sensitive to changes in investment specific technol-

ogy than the consumption-good sector. In other words, an improvement in the technology producing physical capital induces a considerable increase in R&D activity.

Figure 12 displays impulse response functions to a one standard deviation positive productivity shock, ε_{At} , specific to the consumption-good sector. The impulse response of output in the consumption-good sector is positive and hump-shaped. The response reaches a peak of 1 percent in the fourth period following the occurrence of the shock. While the initial response of the hours worked in the consumption-good sector is negative and statistically insignificant, it becomes positive in the second period and statistically significant in the fourth period onward. The response of output in the R&D sector is negative in the first two periods but marginally statistically significant only in the first one. The response becomes positive after the third year but remains statistically insignificant in terms of the sign.²⁹

7.2 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 discuss the contribution of the sectoral productivity shocks and the investment-specific shocks to annual fluctuations in economic activity. 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

²⁹The empirical impulse response functions are roughly consistent with most of the main dynamics generated by the economic model. We would like to stress that although the model has potential to generate responses closer to the empirical ones, both in terms of magnitude and size if enriched with more core features, its role in this paper remains auxiliary.

the VAR model. The fractions of variances are obtained in simulation blocks in which we only keep active a single shock while the variances of the rest are set equal to zero. Figure 13 displays the distributions of 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. Median values of variance decompositions along with 90 percent confidence intervals are reported in table 3 (means are close to medians).

Productivity shocks specific to the R&D sector explain almost 20 percent of the variability of output in the sector and only 4.4 percent 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 productivity shocks on the output of the non-R&D sector is quite large. In particular, R&D productivity shocks account for 30.2 percent of the variance of output in the non-R&D sector. They also explain a non-negligible portion of the variance of hours in the non-R&D sector in the order of 16.7 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 69.9 percent of its variance. In addition, these type of shocks explain 39.1 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. Specifically, shocks to investment-specific technology explain 35.4 and 31.1 percent of the variability of the non-R&D sector output and hours, respectively. Our results suggest that productivity shocks in the non-R&D sector play only a minor role in driving the fluctuations of output and hours in the two sectors. The largest fraction

explained by consumption-good sector productivity shocks is 13.7 percent for the output of the sector. As regards to the variability of labor productivities, the highest fraction in the R&D and non-R&D sectors is attributed to investment-specific shocks by 56 and 38.4 percent, respectively.

The three technology shocks jointly explain 92.3 percent and 78.5 percent of the variance of outputs in the R&D sector and the rest of the economy, respectively. Ouyang (2011), argues that technology shocks are important factors in explaining the procyclicality of R&D. Our results confirm this claim since the main sources of output volatility in the two sectors, capital investment-specific and R&D productivity shocks, induce output responses of the same sign. Furthermore, technology shocks, jointly explain a moderate proportion of the variance of hours which is in the order of 46.1 percent and 56.4 percent in the R&D sector and the consumption-good sector, respectively. 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.³⁰ These results show that under this specification of the model, investment-specific shocks and neutral productivity shocks explain 40.2 and 33.3 percent of the variability of NIPA output while the combined effect of technology shocks is 90.3 percent; this result is not too different from findings of previous studies that used quarterly data.³¹ The combined effect of technology shocks on productiv-

³⁰In the model of section 3, the R&D channel is closed when $\alpha_1 = 0$.

³¹Altig et al. (2011), 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. Fisher (2006), finds that investment-specific shocks explain 42-67 percent of the variation of output while neutral technology shocks explain 8-33 percent for the period 1955:1-2000:4.

ity and hours increases significantly compared to the model where there is a separate R&D sector and R&D is treated as investment than solely as an expense.

In the second set of results (tables 5 and 6), we compute variance decompositions of the forecast error. The numbers in parenthesis correspond to 90 percent bootstrapped confidence intervals. Although the connection between forecast error decompositions and contributions to cycles is not as direct as that reported in tables 3 and 4, the former roughly confirm the latter regarding the impact of shocks. Over a horizon of 1 to 12 years, investment specific shocks explain a fraction of 44.7 to 69.3 percent of the variance of the forecast error of R&D output while the fraction is increasing with the horizon. Likewise, productivity shocks in the R&D sector explain 18.3 to 30.6 percent of the variation of the output forecast error in the R&D sector. The fraction of forecast error variance for the consumption-good sector output to R&D productivity shocks ranges from 1.2 percent, 1 period ahead, to 35.2 percent, 12 periods ahead. Those decompositions suggest 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 explain most of the variation 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 twelve years, technology shocks jointly explain up to 78.8 percent of the variation of the forecast error of NIPA GDP as opposed to the 100 percent for the two outputs in the extended model.

Tables 7 to 10, display variance decompositions when the alternative measure of labor is used. Compared to the benchmark case, the impact of capital investment-specific

shocks on outputs increases slightly to 73.5 percent for R&D output and 44.8 percent for the consumption-good sector output. The impact of R&D productivity shocks on the output of the non-R&D sector reduces to 18.2 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 labor reduces to 27.3 percent in the R&D sector and 17.4 percent in the non-R&D sector while the combined effect of technology shocks on labor in the non-R&D sector reduces to 35.3 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 the non-R&D sector and R&D investment remain.

8 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 productivity 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, 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 productivity in the R&D sector and capital investment-specific technology along with changes in 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 exactly 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 productivity 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 also confirm Ouyang's (2011) proposition that technology shocks are key factors in explaining the procyclicality of R&D.

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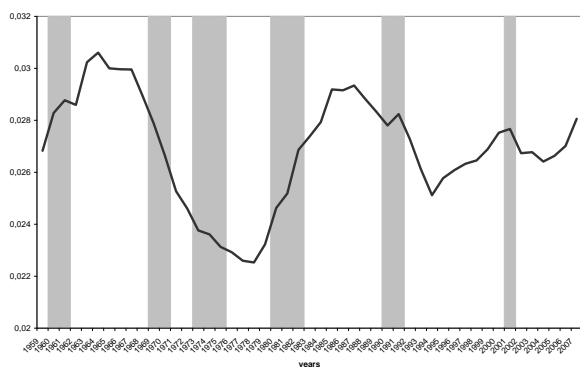


Figure 1 - Share of R&D investment in
(adjusted) GDP

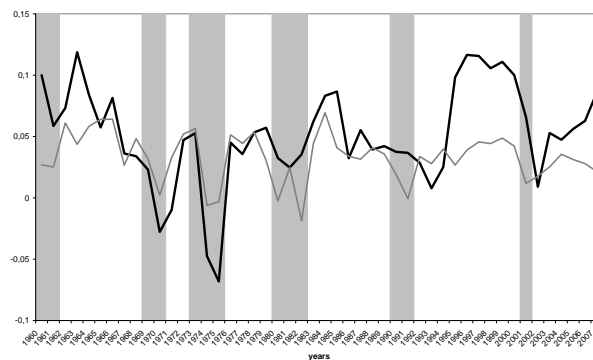


Figure 2 - Growth rates of real R&D investment
(black) and adjusted real GDP (grey)

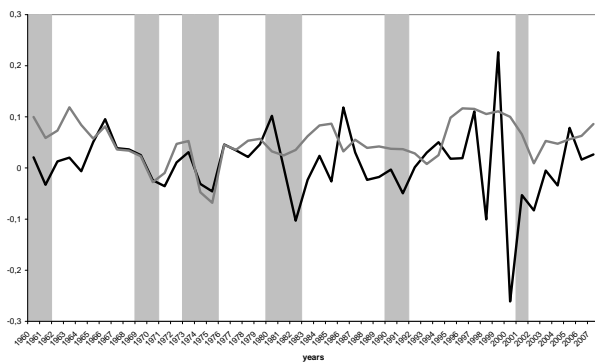


Figure 3 - Growth rates of real R&D investment
(grey) and R&D employment (black)

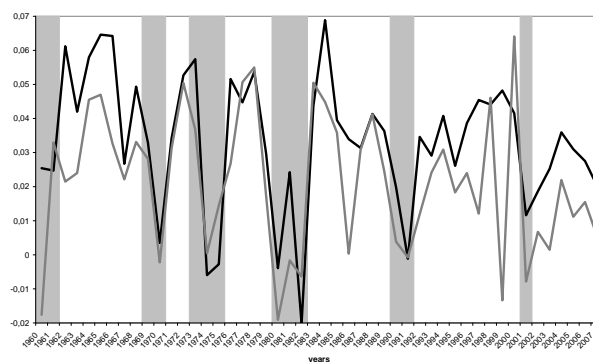


Figure 4 - Growth rates of net of R&D real
output and net of R&D employment

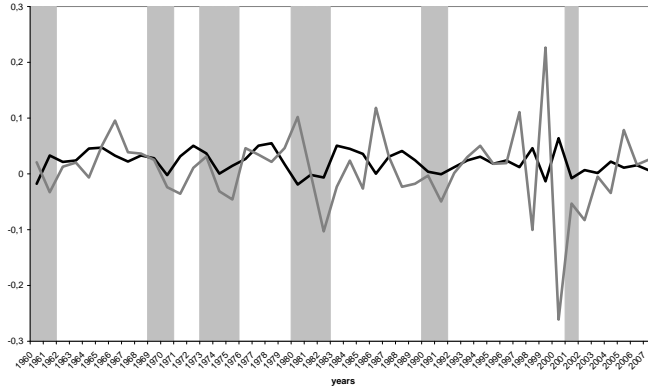


Figure 5 - Growth rates of employment in the non-R&D (black) and R&D (grey) sectors

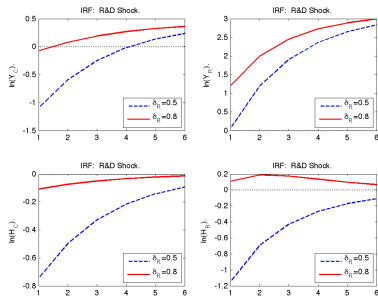


Figure 6 - Theoretical responses to a *positive* productivity shock in the R&D sector

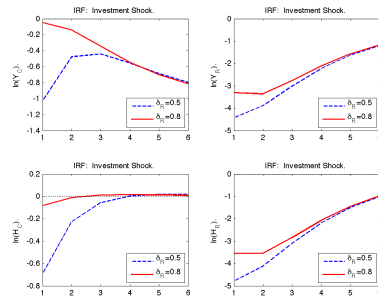


Figure 7 - Theoretical responses to a *negative* investment-specific shock

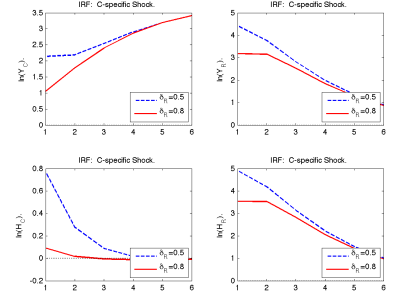


Figure 8 - Theoretical responses to a *positive* productivity shock in the consumption-good sector

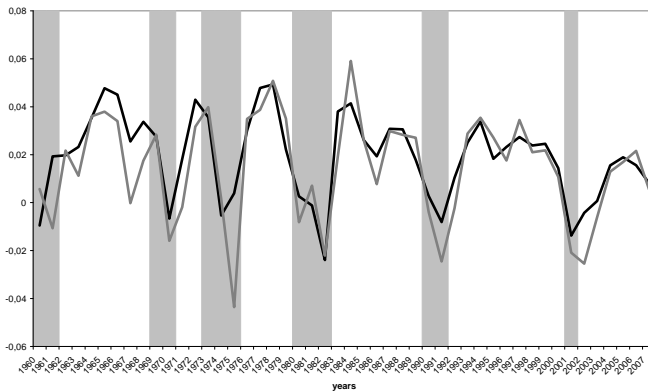


Figure 9 - Growth rates of total hours (grey) and employment (black)

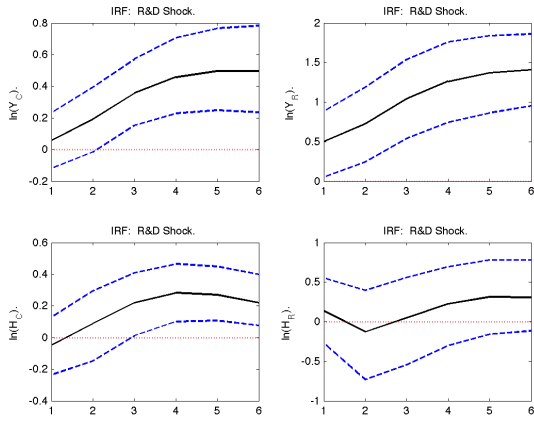


Figure 10 - Response of levels to a *positive* productivity shock in the R&D sector [- - , 90% confidence interval]

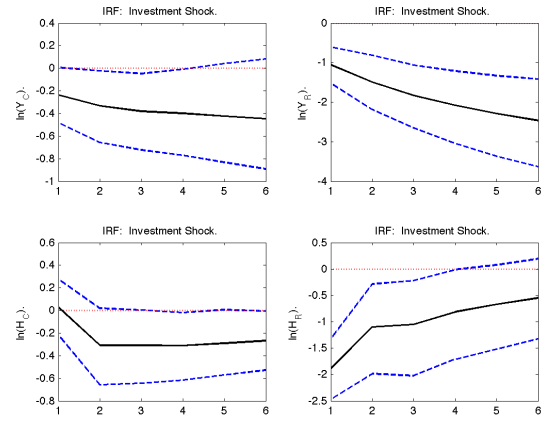


Figure 11 - Response of levels to a *negative* investment-specific shock [- - , 90% confidence interval]

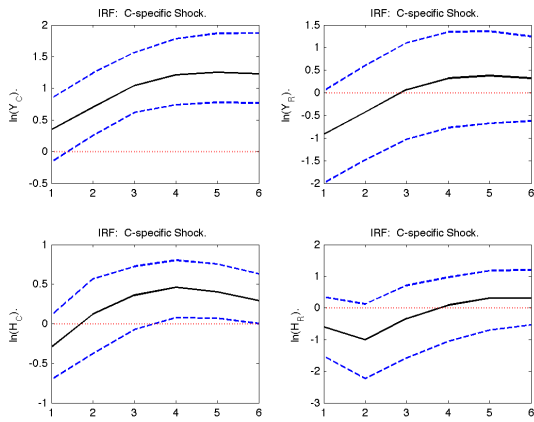


Figure 12 - Response of levels to a *positive* productivity shock in the consumption-good sector [- - , 90% confidence interval]

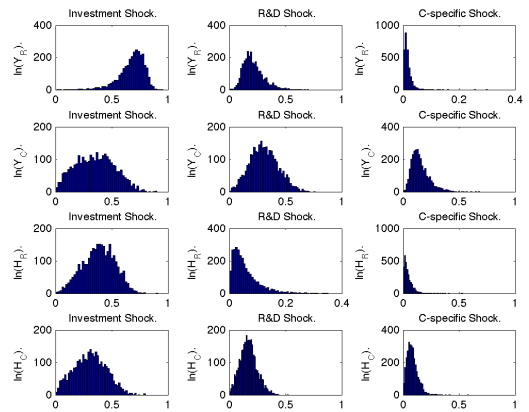


Figure 13 - Distributions of variance decompositions

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

	real adj. GDP	total employment	R&D investment	R&D employment
<i>Volatility</i>	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	\tilde{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)

Shocks \ Sectors	Productivity		Hours		Output	
	R&D	C-sector	R&D	C-sector	R&D	C-sector
Investment	56 (39,69.8)	38.4 (14.6,60)	39.1 (19.1,56.9)	31.1 (11.7,49.4)	69.9 (53.1,80.1)	35.4 (12.3,58.5)
R&D	12.8 (6.5,22.5)	23 (9.5,42.8)	4.4 (1.2,12.1)	16.7 (7.5,27.4)	19.7 (11.4,33.8)	30.2 (15.1,47.9)
C-specific	1 (0.3,3.2)	12.5 (5.1,33.9)	3.2 (0.9,9.2)	7.4 (2.7,14.7)	1.2 (0.4,3.1)	13.7 (7,25.8)
All Technology	74 (56.4,84.3)	79 (58.6,89.8)	46.1 (27,62.6)	56.4 (35.5,71)	92.3 (82.6,96.3)	78.5 (54.8,89.9)

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

	Productivity	Hours	Output
Investment	39.9 (10.5,66.9)	33.3 (9.9,55.2)	40.2 (14,66.5)
Neutral	31.1 (12.2,68)	13 (4.7,25.8)	33.3 (17.9,55.4)
All Technology	85.8 (56.5,96)	68.8 (47.6,84.1)	90.3 (73.8,97)

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

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

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

Table 6 - Forecast error decompositions of hours (percent)

Year	R&D Hours			C-sector Hours with R&D			Hours without R&D				
	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	R&D	All Tech.	Neutral	Invest.	All Tech.
1	1.5 (0.8,7)	39.1 (22,51.7)	0.4 (0,6)	41 (26.3,55.5)	6.6 (0.1,25.7)	0.1 (0,14.7)	0.9 (0,16.1)	7.6 (2.3,35.8)	5.8 (0.1,22.2)	6.5 (0.1,23.8)	12.3 (2,34.5)
2	10.6 (0.2,34.6)	33.1 (2.5,59.9)	0.8 (0.0,19.4)	44.5 (17.8,71.6)	1.8 (0,23.3)	31.1 (0.5,56.6)	4.5 (0.30.8)	37.4 (9,72.2)	1.4 (0,31.1)	23.8 (0.7,50.8)	25.2 (4,59)
3	1.8 (0,20.9)	46.9 (2.7,71.8)	0.2 (0,20.9)	48.9 (14.3,78.5)	14.9 (0.3,32.7)	28.6 (0.6,57.5)	26.8 (0.8,45.6)	70.2 (20.8,86.3)	12.4 (0.1,45.2)	39.0 (1.6,65)	51.4 (9.2,79.9)
6	6.2 (0,30.4)	49.6 (0.8,71.9)	28.5 (0.3,46.1)	84.3 (18.7,90.6)	15.1 (0.4,32.4)	33.6 (1.5,61.2)	41.3 (7.9,55.6)	90 (40.5,93.1)	54.3 (4.4,75.4)	24.7 (0.6,54)	79 (26.2,89.2)
12	1.2 (0.1,36.2)	61.2 (0.7,72.2)	4.9 (0.2,47)	67.2 (26.6,90.2)	0.3 (0,28.4)	61 (1.5,73.4)	14.1 (0.2,44.5)	75.4 (27.1,90)	9.5 (0.4,74.1)	36.3 (0.2,58.5)	45.8 (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*

Shocks\ Sectors	Productivity		Labor		Output	
	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
	(36.9,74)	(29.2,73.7)	(11.4,51.8)	(5.7,39)	(55.8,82.8)	(22.2,62.2)
R&D	20.2	24.3	7.2	11.3	19.5	18.2
	(10.8,35.8)	(12.1,41.5)	(2.4,17.5)	(4.4,22.5)	(11.5,31.9)	(8.5,30.1)
C-specific	1	6.4	4.8	6.7	1.3	6.1
	(0.3,3.1)	(3.3,12)	(1.2,12.5)	(2.2,14.9)	(0.5,3.2)	(2.5,11.8)
All Technology	85.2	88.4	46.7	35.3	94.3	61
	(70.2,92.2)	(64.3,95.5)	(27.9,65.2)	(19.7,53.5)	(84.2,97.4)	(32,80.1)

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
	(6.2,52.3)	(1.8,41.7)	(6.3,50.7)
Neutral	57.9	37.8	36.4
	(28.7,82.2)	(12.9,58.8)	(10.9,58)
All Technology	93.3	66	71.7
	(71.7,97.8)	(40.9,83.6)	(43.1,87.1)

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

Year	R&D Output			C-sector Output with R&D			Output without R&D				
	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	R&D	All Tech.	C-specific	Invest.	All Tech.
1	20.7 (1.2,41.6)	45.1 (14.8,57.6)	12.1 (1.27,5)	77.9 (42.5,85.4)	0.9 (0,13.6)	9.1 (0.1,26.9)	2.9 (0,18.5)	12.9 (3.7,38.6)	1.5 (0,18.4)	5 (0.1,25.4)	6.5 (0.8,32.6)
2	5.8 (0.1,24.4)	64.8 (26.7,74.5)	16.8 (1.8,32.8)	87.5 (51.5,92.7)	0.3 (0,16.6)	12.4 (0.1,42.6)	12.6 (0.1,41.4)	25.3 (6.3,61.6)	63.5 (11.4,85.6)	0.1 (0,17.5)	63.6 (16.1,88.9)
3	0.8 (0,10.8)	68.7 (36.4,77.5)	25 (7.1,41.6)	94.5 (67,96.6)	9.8 (0.1,29.5)	28.2 (0.8,57.7)	0.1 (0,20.3)	38.1 (11.2,71.2)	29.9 (0.6,64.8)	1.3 (0,28.3)	31.2 (4.1,71.1)
6	0.2 (0,3.4)	66 (38.9,78.4)	33.4 (17.6,52.6)	99.6 (87,99.6)	24.4 (4,42.2)	45.2 (9,67.2)	24.1 (1.7,41.6)	93.7 (43.8,98)	0.1 (0.1,56.2)	17 (0.1,55.5)	17.1 (2.6,75)
12	0 (0,1.1)	69.1 (38.1,83)	30.8 (15.5,57.5)	100 (93.9,100)	23.9 (5.7,41.4)	42.8 (5.8,68.7)	33 (7.2,53.5)	99.6 (62.3,99.9)	13 (0.2,72.8)	14.9 (0.1,53)	27.9 (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*

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

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