



A theory of growth and volatility at the aggregate and firm level[☆]

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ARTICLE INFO

Article history:

Received 4 September 2007

Received in revised form

20 October 2009

Accepted 21 October 2009

Available online 20 November 2009

JEL classification:

D9

E3

L1

Keywords:

Endogenous growth

Aggregate volatility

Firm-level volatility

Innovation

ABSTRACT

We present an endogenous growth model that explains the evolution of the first and second moments of productivity growth at the aggregate and firm level during the post-war period. Growth is driven by the development of both (i) idiosyncratic R&D innovations and (ii) general innovations that can be freely adopted by many firms. Firm-level volatility is affected primarily by the Schumpeterian dynamics associated with the development of R&D innovations. The variance of aggregate productivity growth is driven by the arrival rate of general innovations. Ceteris paribus, the share of resources spent on development of general innovations increases with the stability of the market share of the industry leader. As market shares become less persistent, the model predicts an endogenous shift in the allocation of resources from the development of general innovations to the development of R&D innovations. This results in an increase in R&D, an increase in firm-level volatility, and a decline in aggregate volatility. The effect on productivity growth is ambiguous.

On the empirical side, this paper presents new cross-country evidence that R&D subsidies are not significantly associated with higher growth but are associated with lower aggregate volatility. It also documents an upward trend in the instability of market shares, a positive association between firm volatility and R&D spending, and a negative association across sectors between R&D and how correlated the sector is with the rest of the economy.

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1. Motivation

The literature on endogenous growth has made substantial progress in the past 15 years. In spite of these advances, however, there remains much to be learned about the determinants of long-run productivity growth. State-of-the-art models (Aghion and Howitt, 1998, Chapter 12; Dinopoulos and Thompson, 1998; Jones, 1995; Kortum, 1997; Peretto, 1998; Segerstrom, 1998; Young, 1998) predict a positive relationship between the growth rate of productivity and the share of research & development (R&D) in GDP. However, this prediction does not seem to be true for aggregate data in the United States (US) during the post-war period. Fig. 1 illustrates the smoothed growth rate of productivity as well as the evolution of the share of private R&D in GDP as measured by the National Science Foundation (NSF). No clear relationship seems to exist between the two variables.¹ At the sector level, Jones and Williams (1998) also find no significant

[☆] We thank Ted Rosenbaum and Kristy Mayer for their excellent research assistance. This paper has also benefited from comments by Sergio Rebelo (the Editor), two anonymous referees, Philippe Aghion, Robert Barro, Susanto Basu, Will Baumol, Jess Benhabib, Christian Broda, Steve Davis, Jonathan Eaton, Humberto Ennis, John Fernald, Raquel Fernandez, Mark Gertler, Andreas Hornstein, Boyan Jovanovic, John Leahy, Thomas Philippon, Esteban Rossi-Hansberg, Jaume Ventura, seminar participants at Stern, New York Fed, San Francisco Fed, Richmond Fed, Catolica University, Yale, Chicago GSB, IV Bank of Portugal Conference in Macroeconomics, the Productivity and Macro NBER Summer Institute. Comin thanks the C.V. Starr Center for Applied Economics for its financial assistance. The views expressed in this paper solely reflect those of the authors.

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¹ The lack of relationship between R&D and growth is robust to allowing for lags in the effect of R&D on growth. Examination of TFP growth or output growth results in similar conclusions. In addition, the upward trend in R&D also holds for the share of scientists and engineers in employment and for

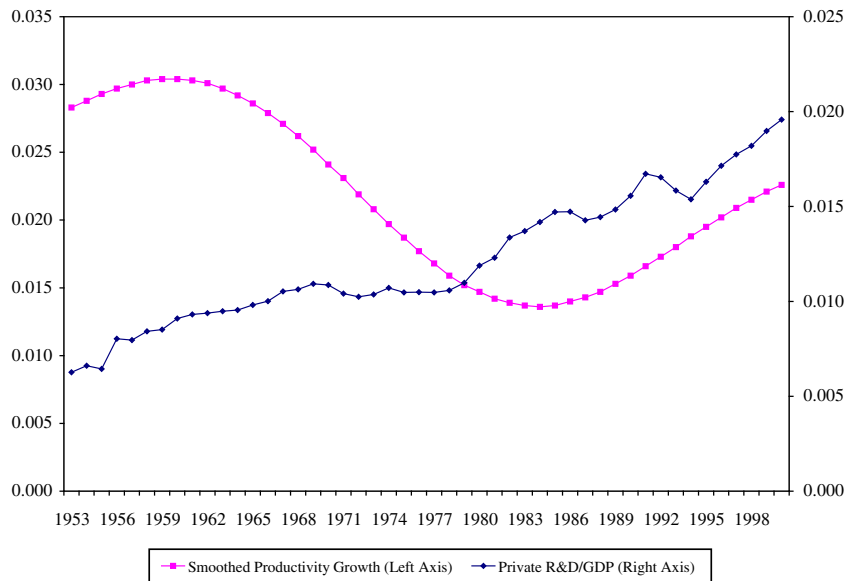


Fig. 1. Evolution of (smoothed) productivity growth and private R&D share in GDP. Note: Productivity growth series is obtained from the BLS. The productivity growth series has been smoothed with a band-pass filter that keeps fluctuations associated with cycles of period greater than 30 years. Private R&D data is sourced from the NSF.

relationship between R&D intensity and TFP growth in the US once sector-level fixed effects are introduced. At the firm level, however, Griliches (1980, 1986) and Griliches and Mairesse (1984) have examined the effect of these same measures of R&D intensity on productivity and TFP growth and have observed a strong positive association even after including firm-level fixed effects.

This paper builds an endogenous growth model that provides an explanation for the varying relationship between R&D and productivity growth at different aggregation levels. The key feature of our model is that, in addition to the standard R&D innovations modelled in Romer (1990) and Aghion and Howitt (1992), it introduces a different type of innovation that we call general innovations (GIs). Like the standard R&D innovations, general innovations are also non-rival. However, two important properties differentiate GIs from R&D innovations. First, a firm that develops a general innovation cannot appropriate the benefits other firms enjoy when they adopt it. This is the case because general innovations—such as managerial and organizational innovations, improved process controls, product development, testing practices and pre-production planning, new personnel and accounting practices, financial innovations, the use of electricity as the source of energy in a plant, etc.—are not embodied in a product and therefore are hard to patent and relatively easy to reverse-engineer.^{2,3} As a result, (i) the inventor of a GI cannot sell it to other firms and (ii) he only benefits from it because the efficiency of production of his firm improves by using the new GI.

A second important property of GIs is that, as illustrated by the examples above, they provide solutions to problems that affect firms in most sectors. Hence, their development improves the productivity of many firms across many different sectors. This contrasts with the productivity improvements associated with new R&D innovations, which are, for the most part, confined to a specific sector.

These two properties of GIs, generality and limited appropriability, have interesting implications. First, a firm's incentives to develop a GI depend on the value of the productivity gain from implementing the innovation at the firm. These productivity gains are more valuable in larger (i.e. leading) firms. As a result, general innovations are typically developed by leading firms.

In equilibrium, there is a negative relationship between resources spent on R&D and resources spent on the development of general innovations. Since (1) R&D leads to turnover in market leaders and to a decline in the value of leading firms and (2) the private return to a GI increases in the value of the firm, a force that leads the economy to invest more in R&D (such as a R&D subsidy) induces a decline in the rate of development of GIs.

(footnote continued)

total R&D expenses in the US and in the OECD. When public R&D expenditures are included into the R&D series, the increase in R&D intensity during the post-war period prevails, although it is more abrupt. The overall contribution of public R&D to growth has been quite small (Griliches, 1987).

² See Table 1 for a longer, albeit incomplete, list of general innovations. For a description of the innovations, see Appendix 2.

³ Hellwig and Irmen (2001) and Boldrin and Levine (2000) have also highlighted the importance of innovations that are not patentable. The innovations that they model, however, differ from our GIs in that they are embodied and innovators accrue revenues from the sale of goods that embody the innovation, as is the case in standard endogenous growth models.

Table 1
Examples of general innovations.

Innovation	Date	Importance	Market leader?
MANAGEMENT AND PRODUCTION DESIGN			
Mass production	1900	Fixed costs spread out over larger volumes meant lower costs.	Yes
Scientific management	1911	Scientific approach to production processes improved productivity.	
Ford assembly line	1913	Shorter assembly time resulted in lower production costs.	Yes
McKinsey management consulting	1923	Streamlined approach to consulting services.	
Multi-divisional structure	1920's	Introduced autonomous divisions responsible for pursuing goals independent of each other.	Yes
Just-in-time manufacturing	1950's	Improved synergies between adjacent production processes to minimize inventories.	
HUMAN RESOURCE MANAGEMENT			
Hawthorne studies	1924–1933	Highlighted the importance of the relationship between the employee morale and productivity.	Yes
Survey feedback	1940's	Highlighted the importance of sharing feedback with employees.	
Sensitivity training	1946	Focused on the importance of open discussion in small groups.	
Industrial psychology	1940's–50's	Emphasized contextual variables for purposes of training and positive organization change.	
CREDIT/BANKING			
Credit card	1950	Helped businesses and consumers undertake credit transactions in a more extensive and systematic manner.	Yes
Electronic recording method of accounting	1950's	Helped computerize the banking industry.	Yes
Magnetic ink character recognition	1950's	Allowed computerized tracking and accounting of check transactions.	Yes
Electronic money	1972	Introduced an electronic alternative to check processing.	Yes
COMPUTER/SOFTWARE/INTERNET			
Computers	1936	Enabled the automation of an assortment of functions.	
Hypertext	1945	Basis of the eventual World Wide Web.	
Fortran	1957	High-level programming language that made for improved scientific, engineering and mathematical applications.	Yes
Arpanet	1969	Enabled the exchange of information over large geographic distances.	
Internet search engines	1990	Greatly reduced cost and increased convenience of gathering of information.	
Internet shopping	1990's	Provided firms with a new avenue to conduct their business.	
TRADE			
Department store	1877	Improved the efficiency of retail and distribution.	
Mall	1922	Started the modern-day one-stop shop for all consumers.	Yes
MARKETING			
Mail order catalog	1872	Enabled businesses to target consumers that did not access to retail outlets.	
Coupons	1895	Effective promotion/marketing tool.	Yes
CHEMICAL ENGINEERING			
Chemical engineering	1920's	Improved the design and control of similar operations at plants in several different industries.	

This trade off between R&D and GIs accounts for the trends observed in productivity growth at the aggregate level. Productivity growth increases with the development of both R&D and general innovations. However, since an increase in R&D intensity leads to a decline in the arrival rate of general innovations, the actual relationship between R&D and productivity growth is ambiguous.

Firm-level growth also depends on the growth of aggregate demand but, more importantly, on the change in the firm's market share. GIs affect all firms in a relatively symmetric way, therefore they do not have significant effects on market shares. R&D investments, instead, lead firms to develop new products that replace the current leading products, resulting in significant changes in relative demand and market shares. As a result, firms that engage more intensively in R&D investments are more likely to obtain the capital gains associated with becoming the market leader. This explains the positive association found by Griliches (1984) and Griliches and Mairesse (1984) between R&D investments and growth at the firm level.

One limitation of this theory is that, unlike R&D, there is no time series for the investments in GIs, and therefore, we cannot test the details of the mechanisms directly. Fortunately, since both R&D and GIs arrive randomly over time, our model also has implications for the evolution of the volatility of productivity growth at the firm and aggregate levels. This wealth of predictions can help us test the model.

Specifically, R&D innovations lead to substantial firm-level volatility since incumbents incur losses while entrants enjoy capital gains. An increase in R&D intensity leads to turnover in the market leader and increases firm-level volatility. However, since R&D innovations are to a large extent sector specific, they have only a minor effect on aggregate volatility. Aggregate volatility is primarily affected by the arrival rate of general innovations because these determine the co-movement of growth across sectors by causing simultaneous fluctuations. Hence, a decline in investments in the development of GIs leads to a decline in aggregate volatility.

Consistent with these predictions, McConnell and Perez-Quiros (2000) and Stock and Watson (2003) have shown that the volatility of aggregate variables such as output, hours worked and labor productivity growth has declined during the post-war period. At the same time, the volatility of these same variables in publicly traded firms has doubled during the post-war period, as found by Comin and Mulani (2004), Comin and Philippon (2005) and this paper.⁴

In Section 3, we provide further empirical evidence consistent with the forces and mechanisms emphasized by the model. First, we document an increase in the subsidies to R&D innovations over the post-war period. Second, we provide cross-country evidence that R&D subsidies do not lead to faster growth but lead to lower aggregate volatility. Third, we show that market turnover and firm volatility have increased by more in sectors where R&D intensity has increased by more. Fourth, we establish that there has been a substantial decline in the correlation of productivity growth across sectors, also during the post-war period. As shown by Comin and Philippon (2005), this decline is responsible for a majority of the decline in aggregate volatility. Fifth, this paper establishes that R&D is negatively associated with aggregate volatility by showing that sectors that experienced greater increases in R&D also experienced greater declines in the correlation between their own growth and the rest of the economy's. Thus, the increase in R&D leads to lower aggregate volatility.

While there must be other forces that have contributed to the trends in the volatility of listed firms and, especially, in aggregate volatility,⁵ the mechanisms emphasized in our model are quantitatively significant. A calibration of the model shows that it can account for (i) the lack of an aggregate relationship between R&D and productivity growth, (ii) 75 percent of the increase in the firm volatility of listed firms and, (iii) over 40 percent of the decline in aggregate volatility.

The rest of the paper is organized as follows. Section 2 presents the formal model and undertakes the comparative statics exercises. Section 3 discusses and evaluates predictions of the model in both qualitative and quantitative terms. Section 4 concludes.

2. Model

The following describes an endogenous technological change model that delivers endogenous growth and endogenous volatility at the aggregate and firm level. To maximize the clarity of exposition, we present the basic trade off between R&D and general innovations in the context of a one-sector model. We then extend this basic framework to a multisector economy to understand the determinants of the co-movement of growth across sectors, which is essential for the evolution of aggregate volatility.

2.1. Basic set up

Preferences: The representative consumer enjoys a utility flow that is linear on the units of final output consumed, c_t . The present discounted value of utility is represented as:

$$U = \int_0^{\infty} c_t e^{-rt} dt \quad (1)$$

where r denotes the instantaneous discount rate.⁶ Consumers inelastically supply a mass of L units of labor. They also pay some lump sum of taxes, T_t .

⁴ Recent work by Davis et al. (2006) has shown that non-publicly traded companies have experienced a decline in their volatility since the mid-1970s. This fact provides important information about the sources of firm volatility and in Section 3.3 we discuss how it is consistent with our model.

⁵ We discuss some of these complementary explanations in Sections 3.3 and 3.4.

⁶ As in many other endogenous growth models, it is trivial to replace the linear utility function by a concave one. In this case, the Euler equation pins down the equilibrium interest rate of the economy. (Note that in equilibrium, the expected growth rate of consumption is the same as the expected growth rate of output.)

Production: We initially assume the economy is comprised of one sector that competitively produces y_s units of output with price p_s . Output is produced by combining $m + 1$ intermediate goods, where m is a constant. Each intermediate good is produced by one and only one producer. Intermediate goods can be of two types. The good with highest quality, q , is the leading intermediate good. Consumers perceive this as a differentiated intermediate good because of its superior technical properties. The rest of the producers cannot compete with the leading intermediate good and must produce standard, undifferentiated intermediate goods.

Let x^l denote the number of units of the leading intermediate good employed to produce output. Similarly, let x_i^f denote the number of intermediate goods employed by the i th standard producer. Then the production function can be expressed as:

$$y_s = q \left(\beta (x^l)^\alpha + (1-\beta) \left(\sum_{i=1}^m x_i^f \right)^\alpha \right)^{1/\alpha} \quad (2)$$

where q is the quality of the leading intermediate good, $\beta < 1$ is the market share of the leading intermediate good, and $\alpha \in (0, 1)$ is the elasticity of substitution between the leading good and the composite of standard intermediate goods.⁷

The production of a unit of intermediate good requires a units of labor. a declines with the efficiency of the production process, h , such that:

$$a = 1/h \quad (3)$$

Innovation: Intermediate good producers can undertake two types of innovations. First, they can attempt to develop an intermediate good of a quality higher than q . In particular, after spending a share n_i^q of aggregate output, they face a probability $\lambda_i^q = \bar{\lambda} n_i^q / (1 - s_{R\&D})$ over an instantaneous time-interval dt of developing a new leading good with quality $\delta_q q$ ($\delta_q > 1$).⁸ In this formulation, $\bar{\lambda}$ measures the probability of succeeding in the development of a superior intermediate good per fraction of output spent on R&D. $s_{R\&D}$ denotes a R&D subsidy that is financed by the lump sum taxes paid by consumers. When a standard intermediate good producer succeeds in his R&D efforts, he becomes the new leading intermediate good producer, and the former market leader becomes a standard intermediate good producer.⁹

Second, intermediate goods producers can also invest in improving the production process of their intermediate good (i.e. reducing the cost of production, a). Specifically, they can invest a share n_i^h of aggregate output and face an instantaneous probability $\lambda_i^h = \bar{\lambda} (n_i^h)^{\rho_h}$, with $0 < \rho_h < 1$, of successfully increasing h to $\delta_h h$, with $\delta_h > 1$. We denote these types of production improvements as general innovations. For future reference, it is useful to define $c(\lambda) \equiv (\lambda/\bar{\lambda})^{1/\rho_h}$ as the share of aggregate output that a producer must invest to face a probability λ of developing a general innovation.

These two types of innovations differ in their appropriability. Firms that invent a new product or improve the quality of an existing product can patent the innovation and extract a substantial fraction of the surplus enjoyed by other firms from such an innovation. On the other hand, firms that develop GIs, such as improvements in management practices, cannot appropriate the benefits experienced by other firms that use the innovations. Appropriating this surplus is impossible because GIs are easy to reverse engineer and because they are difficult to patent, since most of them are not embodied in a good. These characteristics are reflected in the assumption that all producers immediately (and costlessly) adopt GIs.

A second difference between the two types of innovations that will be important in the multisector extension is their applicability. The impact of new or improved goods is often restricted to a small number of sectors, whereas GIs, such as improvements in management or in the organization of production, can be applied to many different economic activities across a wide array of sectors.

Government: The government collects lump sum taxes from the consumers to finance the exogenous R&D subsidy at every instant.

2.2. Analysis

We start by exploring the pricing problem of intermediate good producers. The leading intermediate good producer faces an isoelastic demand function and sets a price, p_x^l , equal to the marginal cost times a markup given by the inverse of the elasticity of demand (i.e. $1/\alpha$). Bertrand competition between standard intermediate good producers brings the price of standard intermediate goods, p_x^f , down to their marginal cost of production. These arguments are reflected in the following expressions, where w denotes the wage rate:

$$p_x^l = \frac{aw}{\alpha} \quad (4)$$

$$p_x^f = aw \quad (5)$$

⁷ Note that this formulation incorporates an externality from the quality of the leading intermediate good to the productivity of the standard intermediate goods. This assumption biases the results against our conclusion but makes the analysis slightly less cumbersome.

⁸ Griliches (1984) finds evidence in favor of the linearity of the R&D production technology using firm-level data.

⁹ This formulation of the R&D dynamics has several interesting features. First, the lower demand elasticity of the leading intermediate good is instrumental in generating cross-sectional variation in sales per worker. Second, by not having to carry around the distribution of qualities for intermediate goods, we can solve the model analytically. Third, the absence of entry and exit simplifies the computation of firm-level moments.

The price of sectoral output is then given by:

$$p_s = \frac{wa}{\zeta q} \quad (6)$$

where $\zeta \equiv [(\beta\alpha^\alpha)^{1/(1-\alpha)} + (1-\beta)^{1/(1-\alpha)}]^{(1-\alpha)/\alpha}$. Expression (6), together with the choice of numeraire, determines the wage rate. Plugging the prices into the demand functions, we can solve for the share of each producer's sales in nominal output¹⁰:

$$\frac{p_x^l x_s^l}{p_s y_s} = \frac{1}{\alpha} \left(\frac{\alpha\beta}{\zeta^\alpha} \right)^{1/(1-\alpha)} \equiv \kappa^l \quad (7)$$

$$\frac{p_x^f x_s^f}{p_s y_s} = \frac{1}{m} \left(\frac{1-\beta}{\zeta^\alpha} \right)^{1/(1-\alpha)} \equiv \kappa^f \quad (8)$$

To explore the investment decisions, it proves useful to introduce some notation. Let v^l and v^f denote, respectively, the market value of the leading and standard intermediate good firms, both divided by nominal output.

Producers of standard intermediate goods can try to develop a new leading intermediate good by undertaking R&D investments. The share of output invested by standard intermediate good producers in developing R&D innovations is determined by the following arbitrage condition:

$$\underbrace{\text{Marginal cost}}_{(1-s_{R\&D})} = \underbrace{\text{Expected Mg. benefit from R\&D innovations}}_{\bar{\lambda}(\delta_q v^l - v^f)} \quad (9)$$

The left-hand side in (9) is the private cost of investing one percent of output in R&D, whereas the right-hand side is the expected marginal benefit from such an investment. With probability $\bar{\lambda}$ the follower experiences a capital gain given by the difference between the value of succeeding in developing a new leading good, $\delta_q v^l$, and the value of a follower in the absence of such an innovation, v^f .

As shown in Appendix 1, the optimal pricing and R&D investment decisions of standard intermediate good producers imply that, in the symmetric equilibrium, the value of standard intermediate goods firms, v^f , is zero. Intuitively, since they charge a price equal to the marginal cost of production, they incur losses equal to the cost of undertaking innovations. The linearity in the R&D technology implies that the losses from the R&D investments are exactly compensated by the expected capital gains from becoming market leaders, making the net value of a standard intermediate good producer zero.

The current market leader can also invest in R&D innovations. He faces the same marginal cost of innovation as followers, but the expected marginal benefit is $\bar{\lambda}(\delta_q - 1)v^l$ instead of $\bar{\lambda}\delta_q v^l$. Since $v^l > v^f = 0$, Eq. (9) implies that the expected marginal benefit of R&D innovations for the leader is lower than the marginal cost of conducting these innovations. As a result, the market leader does not conduct R&D innovations in equilibrium.

This result is clearly unrealistic since market leaders *do* conduct much of the private R&D in the data. However, it is easy to see that market leaders will conduct R&D in equilibrium if they face diminishing returns in the R&D technology. In Appendix 1, we solve this version of the model and show that all the other results hold true.

The market leader has incentives to develop general innovations that reduce the marginal cost of producing intermediate goods for all producers. In an interior solution, the optimal investment in GIs by the leader results in the following equality:

$$\underbrace{\text{Marginal cost}}_{c'(\lambda^h)} = \underbrace{\text{Mg. benefit from general innovations}}_{(\delta_h - 1)v^l} \quad (10)$$

The left-hand side of (10) is the cost of increasing the probability of developing a general innovation by one percent, whereas the right-hand side is the market leader's private benefit from the arrival of a GI. This is given by the market value of the leader times the gain in productivity from the arrival of the GI, $\delta_h - 1$. Note that, since GIs cannot be sold, their private return is proportional to the value of the firm that develops them. Followers, in principle, can also come out with general improvements in productivity. In equilibrium, however, since the private value of these innovations is proportional to the value of the firm, and v^f is equal to zero, followers do not undertake general innovations.¹¹

To close the model, we just need to determine the value of the market leader, v^l , which is given by the following asset equation:

$$rv^l = (1-\alpha)\kappa^l - c(\lambda_h) + \lambda^h(\delta_h - 1)v^l - \lambda^q v^l \quad (11)$$

¹⁰ Combining the demands for each intermediate good and the labor market clearing condition allows us to solve for the number of units of each type of intermediate good sold:

$$x^l = \frac{1}{a[1 + ((1-\beta)\alpha/\beta)^{1/(1-\alpha)}]} L$$

$$x_i^f = \frac{((1-\beta)\alpha/\beta)^{1/(1-\alpha)}}{a[1 + ((1-\beta)\alpha/\beta)^{1/(1-\alpha)}]} \frac{L}{m}$$

¹¹ Table 1 and Appendix 2 provide evidence that GIs are mostly developed by market leaders.

Eq. (11) says that the expected income generated by a license on the leading product during a unit interval, rv^l , is equal to the instantaneous profit flow net of the costs of investing in GI, $(1-\alpha)\kappa^l - c(\lambda^h)$, plus the expected capital gain from succeeding in developing a GI, $\lambda^h(\delta_h - 1)v^l$, minus the expected capital loss from being replaced as market leader by a standard intermediate good producer, $\lambda^q v^l$.

Solving for v^l yields the following expression:

$$v^l = \frac{(1-\alpha)\kappa^l - c(\lambda^h)}{r + \lambda^q - \lambda^h(\delta_h - 1)} \tag{12}$$

where the numerator reflects the profit flow and the denominator reflects the time preference, r , the creative destruction effect, λ^q , and the expected gains from the development of GIs, $\lambda^h(\delta_h - 1)$.

The optimal investments in R&D (i.e. Eq. (9)) and general innovations (i.e. Eq. (10)) govern the dynamics of the economy. Note in particular that, since there is no state variable, the economy converges immediately to the new equilibrium (λ^h, λ^q) following any disruption in a parameter.

The model can be used to explore the comparative statics of the investment intensities in R&D and GIs with respect to the R&D subsidy ($s_{R\&D}$) and the efficiency of R&D investments ($\bar{\lambda}$). Condition (9) implies that $v^l = (1 - s_{R\&D}) / (\bar{\lambda} \delta_q)$. Plugging this back in condition (10) results in the following expression for λ^h :

$$c(\lambda^h) = \frac{(1 - s_{R\&D})(\delta_h - 1)}{\bar{\lambda} \delta_q} \tag{13}$$

The convexity of $c(\cdot)$ implies that the arrival rate of GIs, λ^h , decreases with $s_{R\&D}$ and with $\bar{\lambda}$. Intuitively, increases in $s_{R\&D}$ and $\bar{\lambda}$ reduce the marginal private cost of developing an embodied innovation. Restoring the equilibrium in the arbitrage condition requires a decline in the value of the market leader. This decline in v^l reduces the marginal private return from developing GIs. As a result, the arrival rate of GIs (λ^h) declines.

The response of λ^q to increases in $s_{R\&D}$ and $\bar{\lambda}$ can be explored by substituting the expression for v^l in the arbitrage equation (9) as follows:

$$(1 - s_{R\&D}) = \bar{\lambda} \delta_q \frac{(1-\alpha)\kappa^l - c(\lambda^h)}{r + \lambda^q - \lambda^h(\delta_h - 1)} \tag{14}$$

Increases in $s_{R\&D}$ and $\bar{\lambda}$ require a decline in v^l to restore the arbitrage condition. The Envelope Theorem implies that $\partial v^l / \partial \lambda^h = 0$. Therefore, an increase in λ^q is the only way to bring down v^l and restore the arbitrage condition.

The arrival rate of R&D innovations, λ^q , depends both on the exogenous parameters $s_{R\&D}$ and $\bar{\lambda}$ and on the share of output private agents spend on R&D, n^q . To determine whether increases in $s_{R\&D}$ and $\bar{\lambda}$ lead to increases in the share of private R&D expenditures, λ^q is substituted by $\bar{\lambda} / (1 - s_{R\&D}) n^q$ in (14) and rearranged as follows:

$$1 = \frac{\bar{\lambda}}{1 - s_{R\&D}} \frac{\delta_q [(1-\alpha)\kappa^l - c(\lambda^h)]}{r + \frac{\bar{\lambda}}{1 - s_{R\&D}} n^q - \lambda^h(\delta_h - 1)} \tag{15}$$

Increases in $s_{R\&D}$ or $\bar{\lambda}$ increase the productivity per share of sectoral output spent on R&D today, but also increase the productivity of the followers that will try to take over tomorrow's leader. These two forces are the same; the only difference between them is the timing. The new market leader benefits from the higher productivity of R&D expenses earlier than the producers that will take over in the future. Therefore, as long as the effective discount rate net of the turnover rate (i.e. $r - \lambda^h(\delta_h - 1)$) is positive, the first force dominates and the share of private R&D expenses in GDP, n^q , increases with $s_{R\&D}$ and $\bar{\lambda}$. This parameterization is defined as Condition 1.

Condition 1. $r > \lambda^h(\delta_h - 1)$, where λ^h is defined in (13).

Proposition 1 summarizes our findings thus far.

Proposition 1. *In response to increases in $s_{R\&D}$ or $\bar{\lambda}$, the arrival rate of general innovations, λ^h , declines while the arrival rate of R&D innovations, λ^q , increases. Further, if Condition 1 holds, the share of GDP spent on private R&D, n^q , also increases.*

It follows from Proposition 1 that $s_{R\&D}$ and $\bar{\lambda}$ cause the rate of R&D-driven and general innovations to move in opposite directions. This negative co-movement between R&D-driven and general innovations is one of the two key elements driving the post-war dynamics of growth and volatility at the aggregate and firm level. To introduce the second key element, the analysis needs to be extended into a multisector setting.

2.3. Multisector economy

To move from the one-sector to the multisector economy, we need to determine how sectoral output is aggregated and how applicable are innovations across sectors.

The multisector economy is composed of N sectors. Sectoral output, y_s , is produced according to (2). Final output, y , results from competitively aggregating the N sectoral outputs in the following Cobb–Douglas way¹²:

$$y = \prod_{s=1}^N y_s^{1/N} \quad (16)$$

In terms of the innovations' applicability across sectors, it is important to make a distinction between GIs and R&D innovations. GIs such as innovations in management, sales, personnel, distribution and similar fields can be applied to virtually all sectors of the economy because firms in all sectors need to manage, sell, motivate and coordinate workers and distribute their products and services.¹³ R&D innovations, in contrast, lead eventually to the creation or improvement of a product that increases the productivity of a, often, sector-specific task. Hence, in what follows, R&D innovations are assumed to be sector-specific while, for the time being, general innovations are assumed to diffuse freely and immediately to all the sectors in the economy.¹⁴

This difference in the innovation's applicability is also based on findings uncovered in the empirical section of the paper. Specifically, we explore the generality of GIs and R&D innovations by estimating the effect of R&D on the correlation of growth across sectors. If R&D innovations were general, an increase in a sector's R&D share in sales should lead to higher co-movement between the sector's growth and the rest of the economy. Instead we find the opposite. Hence, given the negative co-movement between R&D and GIs, our evidence supports the greater generality of GIs vis a vis R&D innovations.

The generality of GIs implies that the development of a new GI leads both sectoral and aggregate output to increase by a factor of δ_h . The sector specificity of R&D innovations implies that the development of a R&D innovation in sector s leads to an increase in y_s by a factor δ_q , but leads to an increase in aggregate output by only a factor of $\delta_q^{1/N}$.

The arrival rate of R&D innovations in sector s is denoted by λ_s^q . λ^h continues to denote the arrival rate of GIs in the economy. Following the same logic as in the one-sector version, it is possible to derive arbitrage and optimal investment in GIs equations very similar to (9) and (10).¹⁵ For the sake of brevity, the details of the derivations are relegated to Appendix 1. An asset equation similar to (11) can be used to determine the market value of the producer of the leading intermediate good in any given sector as:

$$v^l = \frac{(1-\alpha)\kappa^l - c(\lambda^h/N)}{r + \lambda_s^q(1 - (\delta_q^{1/N} - 1)(N-1)) - \lambda^h(\delta_h - 1)} \quad (17)$$

This expression differs from the value of the leader in the one-sector economy in two important aspects. First, now GIs are also developed in other sectors. Therefore, the leader in sector s incurs only the cost of developing a fraction $1/N$ of the GIs developed in the economy, but benefits from an arrival rate of λ^h . Second, now the leader in sector s benefits from the increase in aggregate demand associated with the development of R&D innovations in the other sectors. This reduces the effective discount rate by the term $(\lambda_s^q(\delta_q^{1/N} - 1)(N-1))$.

The arbitrage and optimal investment in GIs equations together with the expression for v^l govern the dynamics of the economy. Given the similarity to the one-sector model, it is possible to specify conditions such that $s_{R\&D}$ and $\bar{\lambda}$ cause λ_s^q and λ^h to move in opposite directions. For brevity's sake, these conditions are specified in Appendix 1, and are assumed to hold henceforth. As was the case before, λ^h declines with $s_{R\&D}$ and $\bar{\lambda}$. The important difference with respect to the one-sector economy is that, since some GIs are developed in other sectors, $\partial v^l / \partial \lambda^h > 0$ at the optimum. In this context, it could be the case that, in response to increases in $s_{R\&D}$ or $\bar{\lambda}$, the decline in λ^h is large enough to necessitate a decline (rather than an increase) in λ_s^q to equalize the marginal cost with the expected marginal benefit from R&D innovations. This is regarded as a pathological case and conditions, stated in Appendix 1, are imposed that rule it out.

The next section computes the first and second moments of the growth rates of output and productivity at the aggregate and firm level and explores their evolution in response to increases in $s_{R\&D}$ and $\bar{\lambda}$.

Aggregate moments: Growth is the result of both embodied and general innovations. For any given sector s , the growth rate of the sector's output (or productivity), γ_{y_s} , is equal to the number of embodied innovations in the sector times the log of their effect on sectoral output, plus the number of general innovations developed in the entire economy times their effect on sectoral output. Formally,

$$\gamma_{y_s} = \gamma_{y/l_s} = \#q_s * \ln(\delta_q) + \#h * \ln(\delta_h)$$

where $\#q_s$ is the number of new embodied innovations developed in the sector during the period, and $\#h$ is the number of new general innovations developed in the economy.

¹² The Cobb–Douglas nature of the aggregate production function implies that the nominal output of each sector represents a $1/N$ share of GDP, regardless of the number of R&D and GIs developed in the sector.

¹³ Indeed, the generality of GIs may be one of the reasons why these innovations are difficult to patent.

¹⁴ The immediacy of diffusion of GIs is clearly just a modelling device. In reality, innovations diffuse slowly but also non-linearly. As a result, there may be strong co-movement of growth across sectors if there is significant overlap in the sectoral diffusion curves.

¹⁵ The only difference that the multisector context introduces in the R&D arbitrage condition is that, because of the sectoral specificity of R&D innovations, the capital gain from the development of a R&D innovation now becomes $\delta_q^{1/N} v^l$, instead of $\delta_q v^l$.

The growth rate of the economy, γ_y , is the average of the sectoral growth rates:

$$\gamma_y = \gamma_{y/l} = \frac{\sum_{n=1}^N \gamma_{y_n}}{N} = \frac{\sum_{n=1}^N \#q_n}{N} * \ln(\delta_q) + \#h * \ln(\delta_h)$$

Given the Poisson arrival rates of new technologies, the average growth rate and average variance of the growth rate of output at the sector and aggregate level are as follows:

$$E\gamma_{y_s} = \lambda_s^q \ln(\delta_q) + \lambda^h \ln(\delta_h) \tag{18}$$

$$E\gamma_y = \lambda_s^q \ln(\delta_q) + \lambda^h \ln(\delta_h) \tag{19}$$

$$V\gamma_{y_s} = \lambda_s^q (\ln(\delta_q))^2 + \lambda^h (\ln(\delta_h))^2 \tag{20}$$

$$V\gamma_y = \frac{\lambda_s^q}{N} (\ln(\delta_q))^2 + \lambda^h (\ln(\delta_h))^2 \tag{21}$$

Several conclusions can be drawn from these expressions. (i) Aggregation does not affect the expected growth rate of productivity since aggregate and sectoral expected growth rates (expressions (19) and (18), respectively) coincide. (ii) Increases in $s_{R\&D}$ or $\bar{\lambda}$ have ambiguous effects on expected growth. In particular, these parameter changes lead to increases in λ_s^q and declines in λ^h and hence to an ambiguous effect on the average growth rate of productivity both at the aggregate and sector levels. (iii) The variance of sectoral growth (expression (20)) also responds ambiguously to increases in $s_{R\&D}$ and $\bar{\lambda}$. (iv) However, this ambiguity disappears when we explore their effect on the variance of aggregate growth (expression (21)). R&D-driven innovations are sector specific and are averaged away at the aggregate level. Hence, their effect on aggregate volatility is smaller than on sectoral volatility. General innovations, on the other hand, are adopted across the economy. Thus, their impact at the aggregate and sectoral level is the same. As a result, for N sufficiently large, the decline in aggregate volatility driven by the decline in λ^h dominates the increase in volatility associated with the higher λ_s^q , and aggregate volatility declines in response to increases in $s_{R\&D}$ and $\bar{\lambda}$. (v) Hence, aggregation does affect the second moments of the growth rate of productivity (expressions (20) and (21)).

Firm-level moments: Expected firm-level sales growth—denoted by $E\gamma_{sales_i}$ —is affected by the rates of arrival of general innovations and R&D innovations in the economy through their effects on aggregate growth, $E\gamma_y$. In addition, producers of standard intermediate goods expect a higher growth rate of sales than market leaders because they invest in R&D, and with probability λ_s^q/m , they will take over the market leader and his sales. Conversely, the current market leader does not invest in R&D and with probability λ_s^q will be taken over by a follower, experiencing a loss in sales. As can be observed below, the distribution of the expected growth rate of sales per worker—denoted by $E\gamma_{sales_i/L_i}$ —only differs from the distribution of the growth rate of sales in the size of the capital gain/loss from market turnover. Hence, at the firm level, the model predicts a positive relationship between R&D intensity and expected growth of sales and sales per worker:

$$E\gamma_{sales_i} = \begin{cases} E\gamma_y - \lambda_s^q \ln(\beta m / ((1-\beta))) & \text{for } i = l \\ E\gamma_y + \lambda_s^q / m \ln(\beta m / ((1-\beta))) & \text{for } i = f \end{cases}$$

$$E\gamma_{sales_i/L_i} = \begin{cases} E\gamma_y - \lambda_s^q \ln(1/\alpha) & \text{for } i = l \\ E\gamma_y + \lambda_s^q / m \ln(1/\alpha) & \text{for } i = f \end{cases}$$

The firm-level volatility of the growth rates of sales and sales per worker depends on the variance of the aggregate growth rate of the economy and the risk of turnover in the market leader. Expressions (22) and (23) present the average variances of the growth rate of sales and sales per worker¹⁶:

$$var(\gamma_{sales_i}) = var(\gamma_y) + \lambda_s^q \left(\frac{1 + \beta(m-1)}{m} \right) \left(\ln \left(\frac{\beta m}{(1-\beta)} \right) \right)^2 \tag{22}$$

$$var(\gamma_{sales_i/L_i}) = var(\gamma_y) + \lambda_s^q \left(\frac{1 + \beta(m-1)}{m} \right) (\ln(1/\alpha))^2 \tag{23}$$

The variance of aggregate output in the US data is approximately two orders of magnitude smaller than the variance of firm-level volatility. Hence, the quantitatively important term is the latter, which is driven by the turnover rate, λ_s^q . An increase in $s_{R\&D}$ or $\bar{\lambda}$ leads to higher turnover, λ_s^q , both directly and through the increased investments in the development of R&D-driven innovations that it triggers. In this way, $s_{R\&D}$ and $\bar{\lambda}$ increase firm-level volatility.

¹⁶ Firm-level variances are weighted by the share of firm sales.

3. Discussion and evidence

We have just shown that the model's predictions are consistent with the facts described in the Introduction. It predicts the lack of a clear relationship between R&D intensity and productivity growth at the aggregate level, the positive association between them at the firm level, the upward trend in firm-level volatility and the downward trend in aggregate volatility. This section accomplishes four things. First, it describes the increase in R&D subsidies during the post-war period. Second, it provides new cross-country evidence that R&D subsidies do not lead to faster growth but lead to lower aggregate volatility. Third, it discusses further theoretical predictions of the model and brings them to the data in order to further check for the empirical relevance of the mechanisms described in the model. Finally, it conducts a calibration exercise to assess the power of the model to generate the dynamics of volatility and growth observed in the data.

3.1. Driving forces

The R&D tax policy in the United States has been implemented through three main initiatives (Hall, 1995). The expensing rules for R&D, introduced in 1954, allowed US firms to expense most R&D expenditures against corporate income for tax purposes. The Economic Recovery Tax Act of 1981 allowed US firms to allocate all R&D expenses against income earned within the country, even if a substantial part of their revenue was generated from foreign sales. In addition, the act introduced the Federal R&D tax credit which allowed firms to deduct from corporate income taxes, in proportion to the established credit rate, a portion of qualified R&D expenditures that exceeded a certain level.

State-level R&D tax credits followed soon after when, in 1982, Minnesota became the first state to introduce such a credit. Since then the number of states offering a R&D tax credit has steadily increased, and 31 states currently offer some form of a tax credit on general, company funded R&D. Not only has the number of states offering a tax credit increased, but the average value of these credits has also grown. Wilson (2005) calculated the effective value of all state-level credits for every year since their inception, taking into account the statutory credit rate, the base amount and whether the credit itself was taxable. He found that the effective average value of the state-level tax credits has grown approximately fourfold since their inception in 1982. Hall and Wosinka (1999) examined the benefit of these federal and state tax credits for US firms. They calibrated the effective R&D subsidy to range between 0.4 and 0.6 depending on whether the firm is subject to state taxation and whether it is eligible for the tax credits.

The increasing level of R&D subsidies leads, in our specification of the R&D technology, to an increasing turnover rate. In addition to the direct effect, R&D subsidies also induce higher private R&D expenses, according to Proposition 1. There is a body of literature devoted to test this prediction, which concludes that R&D tax credits have led to a substantial increase in the share of private R&D in GDP both in the US (Hall, 1993; Mamuneas and Nadiri, 1996) and in other OECD countries (Bloom et al., 2002).

It is important to emphasize that R&D subsidies apply only to R&D expenses. According to the NSF, “R&D consists of activities carried on by persons trained, either formally or by experience, in the physical sciences such as chemistry and physics, the biological sciences such as medicine, and engineering and computer science. R&D includes these activities if the purpose is to do one or more of the following things:

1. Pursue a planned search for new knowledge [...]. (Basic research)
2. Apply existing knowledge to problems involved in the creation of a new product or process [...]. (Applied research)
3. Apply existing knowledge to problems involved in the improvement of a present product or process. (Development)”¹⁷

The NSF also presents a list of activities closely related to our GIs, which are explicitly excluded from the definition of R&D. Among these are social science expenditures, defined as those “devoted to further understanding [of] the behavior of groups of human beings or of individuals as members of groups [in the following areas]: personnel, economics, artificial intelligence and expert systems, consumer, market and opinion, engineering psychology, management and organization, ...”

Therefore, investments in developing general innovations (by-and-large) do not benefit from R&D subsidies.¹⁸

3.2. Productivity growth

Our model predicts an ambiguous effect of R&D on productivity growth at the aggregate and sector level. On the one hand, R&D has a positive effect on the development of patentable R&D innovations while on the other, it has a negative effect on the number of GIs developed in the economy. Abdi and Joutz (2005) provide details about the relationship between R&D and growth. They estimate cointegration relationships between R&D labor, patent applications (i.e. R&D output), and TFP. They find that, while there is a strong and significant positive relationship between R&D labor and patent

¹⁷ Process innovation refers to the development of new industrial processes such as those that lead to the production of steel or chemical products. In our context, this is the same as standard R&D that leads to a new product or an improved version of an existing product.

¹⁸ Rationalizing R&D subsidies goes beyond the scope of this paper. Though R&D has some positive externalities, political considerations may also be involved. Congress, for example, has repeatedly failed to renew the Federal R&D tax credit for longer than one or two years. One rationale for this is that keeping the credit temporary can be used as a carrot for business, and it encourages corporations to make financial contributions to their representatives every year in order to preserve this feature of the tax law (*New York Times*, October 28, 1998).

applications, there is no statistical relationship between patents and TFP. That is, R&D investments produce patents but patent growth fails to have an effect on TFP growth. The lack of a relationship persists after allowing for different leads and lags. These results support the view presented by our model, as Abdih and Joutz (2005) recognize. In particular, their findings constitute indirect evidence in favor of the joint hypothesis that GIs are an important source of productivity growth and that R&D dampens the development of GIs.

We are not the first ones to highlight the importance of general innovations for productivity growth. After studying the importance of the innovations introduced during the last century in the US, Mokyr (2002) claims that “much of the productivity increase in the twentieth century was the result of the perfection of production techniques and process innovation. [...] These led to a continuous transformation in organizational methods, most obviously in mass production, in manufacturing techniques but eventually in services and agriculture as well.”

Unfortunately, direct measures on the intensity of investment in general innovations are not available. This makes it difficult to directly test the negative effect of R&D on the development of general innovations. One imperfect substitute to this exercise consists of creating a list of GIs and noting that most of them were introduced either before World War II or between the 1950s and early 1960s when firm turnover was low. Table 1 provides our (very incomplete) list of GIs, most of which were developed before 1970 by large firms that dominated their markets.¹⁹ Below, we conduct a more systematic test of the negative effect of R&D on GIs investments based on the sectoral variation in second moments.

3.3. International evidence

One way to shed more light on the mechanism emphasized by the model is by taking advantage of cross-country variation in the trends in R&D subsidies. As Bloom et al. (2002) show, in some countries, such as US, Australia and Canada, there have been significant increases in the R&D tax credits between 1979 and 1997, while in others, such as Japan, Italy, the UK, and France, the increments have been much more moderate or even negative. This subsection takes advantage of this variation to explore the association between R&D subsidies and both growth and aggregate volatility.

In particular, we proceed as follows. We measure the increase in the average growth rate of output per worker in each country by the slope of a linear trend in the 5-year moving average of labor productivity growth between 1979 and 1998. Similarly, we measure the increase in aggregate volatility by the slope of a linear trend in the standard deviation of a 5-year rolling window of annual growth rates of labor productivity estimated between 1979 and 1998. Finally, we measure the increase in the R&D tax credits by the difference between the tax component in the user cost of R&D from Bloom et al. (2002) in 1997 and in 1979.²⁰

Of course, when investigating the effect of R&D subsidies on growth, we should control for the mean-reverting tendency of growth identified by the convergence literature. To this end, we control for the average growth in per worker GDP between 1950 and 1978. Fig. 2 displays the partial relation between the increment in the R&D tax credit and the increment in growth. Though positive, this correlation is clearly insignificant. This evidence extends internationally the lack of relationship between R&D and growth found at the aggregate and sector level in the US.

What about the second moments? Is it the case that countries with larger increases in R&D tax credits have experienced larger declines in aggregate volatility as our model predicts? Fig. 3 shows that this is indeed the case. The association between increments in R&D tax credits and declines in aggregate volatility is both large and statistically significant. Hence, this cross-country finding provides further evidence consistent with our model predictions for the relationship between R&D subsidies and the second moments of growth.

3.4. Firm volatility²¹

As described in Section 2, our model rationalizes the increase in firm volatility observed by Comin and Mulani (2004) and Comin and Philippon (2005) in the COMPUSTAT sample. Fig. 4 illustrates the time series of the volatility of productivity growth at the aggregate and firm level. The left axis plots the standard deviation of 10-year centered rolling windows of annual productivity growth. The right axis plots the evolution of the same variable averaged for firms in the COMPUSTAT data base.²² The opposing trends are evident.

It is worth making two remarks about the increase in the volatility of publicly traded firms. First, as shown in Comin and Mulani (2004), the increase in firm volatility in the COMPUSTAT sample is qualitatively and quantitatively robust to conditioning on a firm-level fixed effect, the age of the firm and the size of the firm. To further control for the possibility that the upward trend in firm volatility is driven by a change in the composition of the COMPUSTAT sample, we estimate the following specification for the standard deviation of the growth rate of sales and sales per worker in the firm i over a

¹⁹ A brief description of each technology and why it qualifies as a general innovation is relegated to Appendix 2.

²⁰ Our sample includes France, UK, Italy, Canada, Australia, Japan and the US. These countries, together with Germany, are responsible for an immense majority of world R&D. German unification makes it hard to interpret the country's growth and volatility in the 1990s.

²¹ Consistent with the data, the cross-sectional distribution of firm sizes, measured by employment or by relative sales, in the model is constant over time.

²² For each firm in COMPUSTAT, we compute its volatility in a given year as the centered standard deviation of 10 consecutive annual growth rates of sales per worker. The firm volatility measure plotted in Fig. 4 is the average volatility across firms.

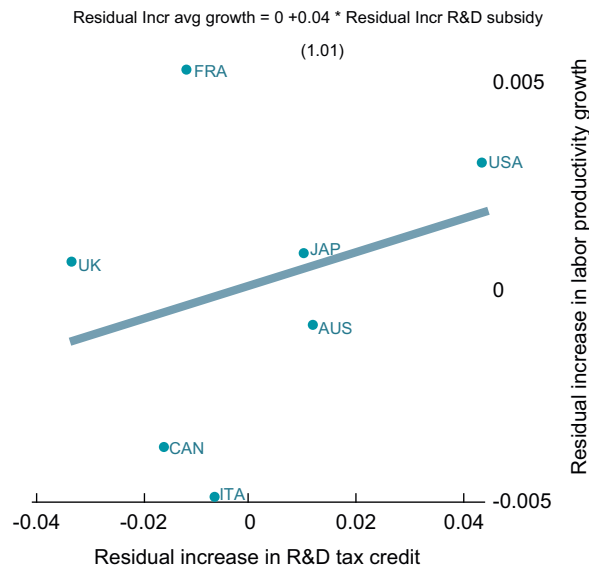


Fig. 2. Cross-country relationship between residual increment in R&D subsidies and residual increment in productivity growth.

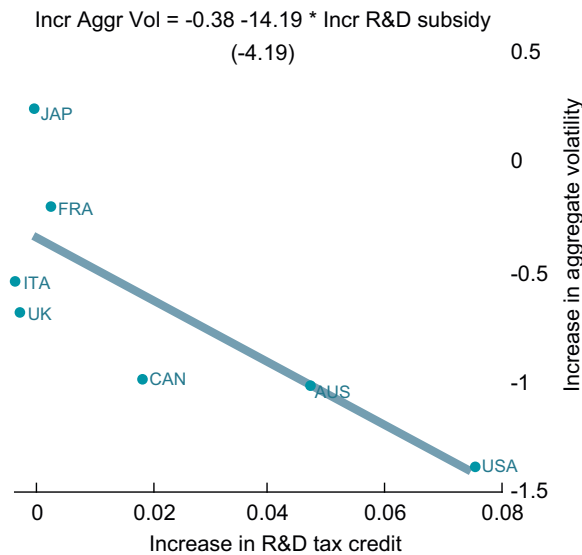


Fig. 3. Cross-country relationship between increment in R&D subsidies and increment in aggregate volatility.

10-year window (σ_{it}):

$$\sigma_{it} = \phi \ln(\text{age}_{it}) + \gamma \ln(\text{sales}_{it}) + \sum_c \alpha_c D_{ic} + \sum_\tau \beta_\tau D_{\tau t} + \varepsilon_{it}$$

In this specification, age_{it} and sales_{it} , respectively, denote the age and real sales of firm i in year t . D_{ic} is a cohort fixed effect which takes a value of 1 for the firms of cohort c and 0 for the rest. $D_{\tau t}$ is a year fixed effect which takes a value of 1 if $\tau = t$ and zero otherwise. To compute the equivalent of a weighted measure of residual firm volatility, observations are weighted by the share of real sales in total sales. Fig. 5 reports the evolution of the estimates of β_τ for the volatility of the growth rate of real sales and real sales per worker. It is quite evident from this figure that the upward trends in firm volatility persist after including the cohort effects.^{23,24} Hence, the increase in firm volatility is not driven by a change in the composition of firms in the COMPUSTAT sample.

²³ Davis et al. (2006) findings are qualitatively similar. The quantitative differences in the slope of the volatility trend may be driven by differences in the age controls.

²⁴ The upward trends are completely robust to including cohort-specific age and size effects in the regression.

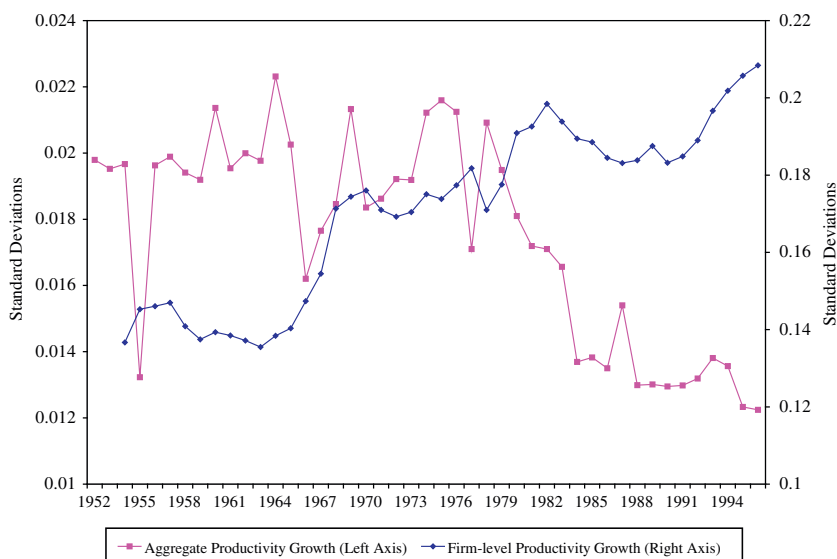


Fig. 4. Evolution of the aggregate and firm-level volatility of productivity. Note: Aggregate productivity growth is sourced from the BLS. Firm-level sales per worker is obtained from COMPUSTAT. Firm and aggregate volatility series are computed as indicated in the text.

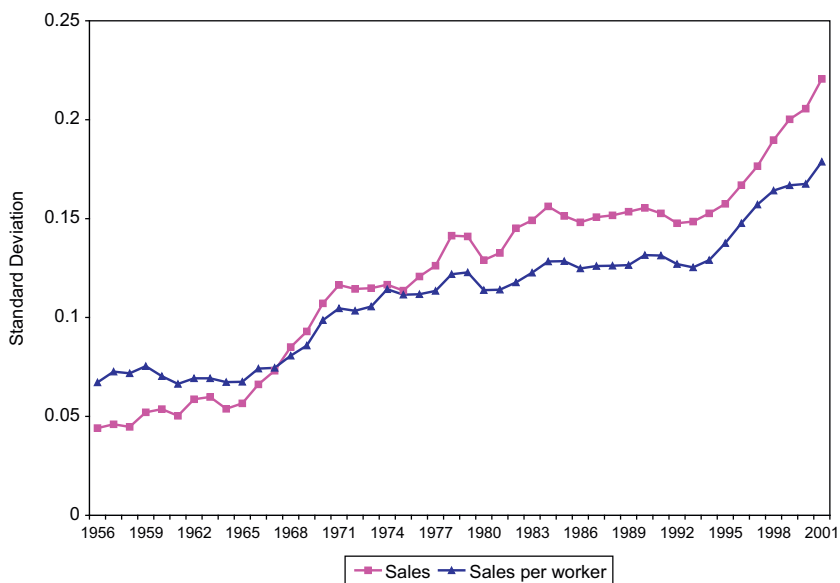


Fig. 5. Firm-level volatility of sales and productivity after controlling for compositional change. Note: Plotted series are the coefficients of year dummies in a volatility regression after controlling for age, size and cohort effects. Source: COMPUSTAT.

In our model, the increase in firm volatility is driven by an increase in the turnover of market leaders, λ_s^q . Comin and Philippon (2005) show that various measures of the turnover rate have increased very significantly.²⁵ Fig. 6, for example, plots a measure of the inverse of the turnover rate for the sample of firms in the COMPUSTAT database. Specifically, for each two-digit sector and year, firms are ranked by the level of sales per worker. After creating a vector of percentiles for every year in the post-war period, persistence in rankings is measured by computing the correlation between the vectors of rankings in two years, five and 10 years apart (i.e. 1950 with 1955 and 1950 with 1960). Repeating the same exercise for all the years in the post-war period results in a time series for the turnover in market leadership.²⁶

²⁵ In particular, Comin and Philippon (2005) document a fivefold increase in the probability that a firm currently in the top fifth of profits or market capitalization in the sector drops from the top fifth in the next five years.

²⁶ This measure of turnover is unlikely to be affected by entry into the COMPUSTAT sample. This is the case because when there are more firms in sample, it is more likely that a firm is taken over by some other firm, but the decline in the percentile associated with this decline in the ranking will be smaller if there were fewer firms in sample.

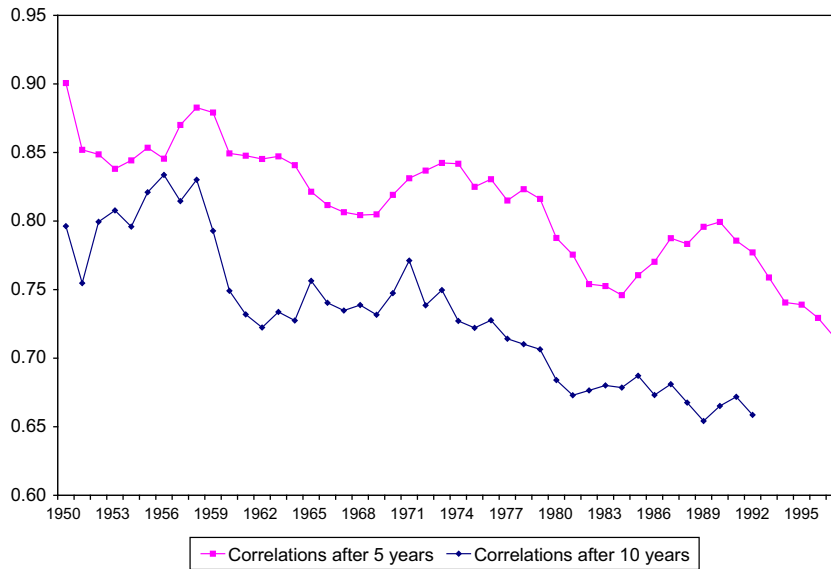


Fig. 6. Correlations of firm percentiles by sales per worker. Source: COMPUSTAT.

Both of these statistics indicate that there has been an increase in market turnover. In the early 1950s, the correlation of rankings was 0.9 for the 5-year-apart measure and 0.8 for the 10-year-apart measure. These correlations have declined in a fairly monotonic manner reaching 0.71 and 0.66, respectively, at the end of the sample in 2002. These numbers can be used to compute, approximately, the turnover rates in our model, λ_s^q .²⁷ In the mid-1950s, λ_s^q was approximately two percent while, in the mid-1990s, it was 2.5–3 times higher. Comin and Philippon (2005) conduct similar exercises using other measures of market leadership, such as profit rates and market value. Specifically, they compute the probability that a firm currently ranked in the top 20th percentile of its sector by profit rates or market value is not in the top 20th percentile in five years. These exercises imply that the turnover rate has increased by a factor of five to six during the post-war period.

These estimates of λ_s^q can be used to calibrate the ability of the model to account for the upward trend in firm volatility. Recall that the variance of the growth rates of sales and sales per worker at the firm level depends on the variance of aggregate growth, $var(\gamma_y)$, and on the turnover rate as follows:

$$var(\gamma_{sales_t}) = var(\gamma_y) + \lambda_s^q \left[\left(\frac{1 + \beta(m-1)}{m} \right) \left(\ln \left(\frac{\beta m}{1-\beta} \right) \right)^2 \right] \quad (24)$$

$$var(\gamma_{sales_t/L}) = var(\gamma_y) + \lambda_s^q \left[\left(\frac{1 + \beta(m-1)}{m} \right) (\ln(1/\alpha))^2 \right] \quad (25)$$

In the US, $var(\gamma_y)$ is approximately two orders of magnitude smaller than the variance of firm-level growth and hence irrelevant to the evolution of firm-level volatility. Our previous estimates imply that the turnover rate in COMPUSTAT in 1950, λ_{s1950}^q , was approximately two percent. The terms in square brackets in (24) and (25) can then be calibrated to match the initial firm volatility in COMPUSTAT.²⁸ Based on the direct estimates in Comin and Philippon (2005) and on the evolution of the private R&D intensity in the US, the turnover rate at the end of the sample, λ_{s2000}^q , is at least between 2.5 and 3 times larger than the initial turnover rate.²⁹ Therefore, the model predicts an increase in firm-level variance by at least a factor of 2.5 or 3. Since firm variance has factually increased by a factor of approximately four in the post-war period, the model can explain at least 62–75 percent of the increase in the variance of firm-level growth.

Cross-sectional variation in relationship between R&D and firm volatility: In addition to having implications for the evolution of firm-volatility, our model has testable predictions about the cross-sectional relationship between R&D and firm volatility. In our model, variation in R&D intensity comes from variation in either $s_{R\&D}$ or $\bar{\lambda}$. Our analysis above implies that sectors where R&D intensity has increased more (i.e. because $s_{R\&D}$ or $\bar{\lambda}$ have increased by more), should experience larger increases in firm volatility and in the turnover rate. In addition, countries where R&D has increased should observe a similar increase in firm volatility. The following analysis shows that the data supports these predictions.

Comin and Philippon (2005) build a panel of annual R&D intensities, turnover rates and average firm volatility in 35 two-digit sectors that cover the US economy from 1950 until 1996. For each sector, they compute the ratio of R&D expenses to total

²⁷ See Appendix 3 for the formal derivation.

²⁸ This implies that the sales and sales per worker of market leaders are approximately 70 percent higher than sales and sales per worker of market followers.

²⁹ Private R&D intensity in the US has increased by a factor of three. In addition, R&D subsidies have increased and the efficiency of R&D expenses has increased. The linearity of the production function for R&D innovations implies that the turnover rate must have increased by, at least, a factor of three.

sales, the median and average standard deviation of a 10-year rolling window of growth in sales and sales per worker, and the persistence in the rankings of sales per worker as in Fig. 6. Then they estimate the following regressions:

$$\lambda_{it}^q = \alpha_{0i} + \alpha_1 t + \beta * (R\&D/Sales)_{it} + \varepsilon_{it}$$

$$\sigma_{it} = \alpha_{0i} + \alpha_1 t + \beta * (R\&D/Sales)_{it} + \varepsilon_{it}$$

These specifications include both a sector-level fixed effect and a time trend to reduce the possibility of spurious correlations between R&D and volatility. In all the cases, they find a positive and statistically significant association between R&D and firm volatility and between R&D and turnover. These estimates are robust to substituting the time trend for time dummies and to controlling for other forces, such as the development of financial markets, that may contribute to firm volatility. Furthermore, the estimated coefficient is economically significant. The increase in R&D intensity accounts for 60 percent of the increase in firm volatility.³⁰

The mechanisms described in our model may also explain the volatility dynamics in other countries. Parker (2006) and Thesmar and Thoenig (2004) have found similar upward trends in the volatility of publicly traded companies in the UK and France. Interestingly, the periods studied by these authors are periods where, as in the US, there was (i) an important increase in R&D subsidies, (ii) an important increase in private R&D intensity and (iii) a decline in aggregate volatility.

Evolution of firm volatility in privately held firms: In empirical evaluation of the model's predictions for firm-level volatility, we have restricted our attention to the sample of publicly traded firms. One reason for this is the scarcity of data on privately held firms. A more substantive reason is that the R&D-driven Schumpeterian dynamics that drive firm volatility in our model, most likely, are only relevant for publicly traded firms. This is the case because R&D expenses of publicly traded firms represent 95 percent of total private R&D expenses in the US. Non-publicly traded firms represent between 40 and 50 percent of aggregate value added, but conduct a very small part of total R&D.³¹ As a result, one would expect that the increased market turnover associated with the increase in R&D expenses would not be a significant factor in explaining the firm volatility of privately held firms.

Davis et al. (2006) have recently analyzed the evolution of employment volatility for US privately held firms since late 1970s. They find that the volatility of non-publicly traded firms has declined during this time. It is obvious that our model does not explain the evolution of volatility for privately held firms. This is the case because (i) the volatility of privately held firms is not significantly affected by R&D, and because (ii) there are other factors that are relevant to explaining the volatility of privately held firms that are orthogonal to our model.^{32,33} In this sense, the relevant test of our theory of firm volatility is clearly the positive conditional correlation observed above between R&D and the volatility of publicly held companies.

It is important to note that, even though our model has nothing to say about the evolution of the volatility of privately held firms, it has important implications for the evolution of aggregate volatility. This is the case because the evolution of aggregate volatility in the US is critically linked to the evolution of the covariance of growth between firms rather than the evolution of firm-level variance. This conclusion follows from two findings. First, as shown in Comin and Philippon (2005), a variance-covariance decomposition of aggregate volatility illustrates that the component that explains all the decline in the variance of aggregate growth is the covariance of growth between sectors rather than the variance of growth within sectors. Second, this holds *a fortiori* when disaggregating all the way until reaching the firm level. Comin and Mulani (2004) conduct a variance-covariance decomposition of growth in the aggregate sales in COMPUSTAT and find that (i) the covariance of growth between firms is 10 times larger than the firm variance component and (ii) the variance of the COMPUSTAT aggregate is driven entirely by the covariance of growth between firms. Following Gabaix (2005), it is natural to hypothesize that, this conclusion would hold *a fortiori* if we included privately held firms which are significantly smaller than publicly traded firms.

As we shall show next, our model provides a testable theory for the determinants and evolution of the covariance of growth in the economy.

³⁰ A significant share of the remaining increase in the volatility of publicly traded firms is likely to be caused by the development of financial markets as hypothesized by Thesmar and Thoenig (2004). Both these authors and Comin and Philippon (2005) provide evidence on this mechanism.

³¹ One reason why privately held firms may not engage in R&D is because their $\bar{\lambda}$ is very low.

³² There are many important differences between publicly and privately held companies. One very significant difference is size. In 2001, 50 percent of US employees worked for firms with 500 employees or more. In the COMPUSTAT sample, instead, over 99 percent of employees worked for firms with over 500 employees. These large firms represented almost 80 percent of all firms in our COMPUSTAT sample. To explain the decline in the volatility of privately held firms, it is necessary to consider mechanisms that drive down firm volatility and that are particularly relevant for privately held firms. One such force may be the improvement of financial markets that now allow privately held firms to better insure their risks. Exploring this or any other hypothesis is beyond the scope of this paper.

³³ One possible criticism is that the NSF underestimates the R&D conducted by privately held companies, especially firms that are not operating yet because they are in the venture capital stage. Though it is possible that the R&D series is not perfect, it is unlikely that the bias due to the mismeasurement of R&D conducted by privately held firms is significant. According to the National Venture Capital Association, venture capital investments represented \$10 billion in 1996. Of course, this is significantly higher than the average during the post-war period and only a small fraction of this was employed in R&D. An upper bound of the R&D share in book equity based on R&D intensive firms in COMPUSTAT would be 10 percent. Hence, the unmeasured R&D from venture capital would be less than \$1 billion. Total private R&D in the US during 1996 was \$134 billion, which makes the potential bias in total private R&D expenditures insignificant. Indeed, the BEA does not even include this in the list of measurement biases encountered in the construction of the Research and Development Satellite Accounts (Okubo et al., 2006).

3.5. Sectoral co-movement

To gain further insight into the evolution of aggregate volatility in our model economy, we can conduct a variance-covariance decomposition of the variance of aggregate growth. Recall that $\gamma_y \equiv \sum_{n=1}^N \gamma_{y_n} / N$. Therefore,

$$V(\gamma_y) = \frac{V(\gamma_{y_s})}{N} + \frac{N(N-1)}{N^2} cov(\gamma_{y_n}, \gamma_{y_{n'}}) \tag{26}$$

where $cov(\gamma_{y_n}, \gamma_{y_{n'}})$ denotes the covariance between the growth rates of two generic sectors n and n' .

In expression (26), as the number of sectors, N , increases, the importance of the sectoral variance in aggregate variance declines, and aggregate volatility increasingly depends on the covariance of growth across sectors. Sectoral variance, $V(\gamma_{y_s})$, depends on the arrival rate of embodied innovations developed in the sector, λ_s^q , and the arrival rate of general innovations developed in the economy, λ^h . The sectoral covariance, on the other hand, is equal to $\lambda^h (\ln(\delta_h))^2$ and depends solely on the hazard rate for general innovations. Therefore, as the number of sectors increases, the variance of aggregate growth increasingly depends on the intensity of general innovations while the arrival rate of R&D-driven innovations becomes less relevant. Further, increases in $s_{R\&D}$ or $\bar{\lambda}$ lead, unambiguously, to declines in the average covariance of growth across sectors and, if the number of sectors in the economy is large, they also induce declines in aggregate volatility.

The covariance of sectoral growth can be trivially decomposed into the product of the standard deviations and correlation of sectoral growth:

$$cov(\gamma_{y_s}, \gamma_{y_{s'}}) = \sqrt{V(\gamma_{y_s})V(\gamma_{y_{s'}})} * corr(\gamma_{y_s}, \gamma_{y_{s'}})$$

When looking at actual data, the variance of growth in a sector typically depends on factors such as the sector size and age. To filter out these effects, it is useful to explore the model implications for the correlation of growth across sectors. The correlation of growth between sectors s and s' depends on λ^h and λ_s^q as follows:

$$corr(\gamma_{y_s}, \gamma_{y_{s'}}) = \frac{\lambda^h (\ln(\delta_h))^2}{\lambda_s^q (\ln(\delta_q))^2 + \lambda^h (\ln(\delta_h))^2} \tag{27}$$

Note that the sectoral correlation is increasing in λ^h and decreasing in λ_s^q . It follows from our previous analysis that increases in $s_{R\&D}$ and $\bar{\lambda}$ lead to declines in the correlation of sectoral growth.

Has the correlation of sectoral growth declined? To explore empirically the evolution of the correlation of growth across sectors, we proceed as follows. First, $corr([\gamma_{s,t}]_{t-4}^{t+5}, [\gamma_{j,t}]_{t-4}^{t+5})$ is defined as the correlation between the annual growth rate in sectors s and j during the 10-year period centered at t . Then, for every sector s , the average correlation with the rest of the sectors is computed as follows:

$$corr_{s,t}^{sec} = \frac{\omega_j^{sec}}{\sum_{j \neq s} \omega_h^{sec}} corr([\gamma_{s,t}]_{t-4}^{t+5}, [\gamma_{j,t}]_{t-4}^{t+5}) \tag{28}$$

where ω_j^{sec} denotes the average share of sector j 's sale in the total sales of the economy. Finally, aggregate correlation is defined as a weighted average of the sectoral correlations:

$$corr_t^a = \sum_s \omega_s^{sec} corr_{s,t}^{sec}$$

Figs. 7 and 8 show a clear downward trend in the average correlation, $corr_t^a$, of productivity and TFP growth across sectors during the post-war period.³⁴ Comin and Philippon (2005) show that the decline in the correlation of sectoral growth is driven by a decline in the covariance of growth across sectors, as opposed to a decline in the variance of sectoral growth. This evidence provides further support for our model, which predicts an unambiguous decline in the covariance of growth across sectors and an ambiguous evolution of the variance of growth at the sector level in response to increases in $s_{R\&D}$ and $\bar{\lambda}$.

Imperfect diffusion of GIs: The basic version of the model predicts no cross-sectional variation in the correlation of growth between sectors because GIs are adopted immediately in all sectors. Now, we enrich the model by relaxing the assumption that GIs are applicable to all sectors in the economy. Specifically, two new assumptions are introduced: (i) the intermediate goods producers of a given sector can freely adopt all general innovations developed in the sector and (ii) the random variable that determines whether a general innovation is suitable to be adopted in a sector other than the one in which it was developed follows a Bernoulli distribution that is independent across sectors and innovations (Figs. 7 and 8).

Let ψ denote the probability that a general innovation is adopted in a sector other than the one in which it was developed. The previous assumptions imply that the arrival rate of general innovations in sector n is equal to $\lambda_n^h + \psi(N-1)\bar{\lambda}_{(-n)}^h$, where λ_n^h denotes the rate of development of GIs in sector n , and $\bar{\lambda}_{(-n)}^h$ denotes the average rate of development of GIs in the sectors other than n .³⁵ The covariance of growth in two sectors, n and n' , depends on how

³⁴ See Comin and Philippon (2005) for more on this downward trend.

³⁵ If GIs do not diffuse perfectly across sectors, sectors that develop fewer GIs also implement fewer GIs. As a result, the model predicts that in sectors with more R&D investments, the contribution to growth from GIs will be lower. Since R&D investments have a direct positive effect on growth, the resulting relationship between R&D and growth will be ambiguous. This is consistent with the insignificant relationship between R&D intensity and TFP growth found by Jones and Williams (1998) in a panel of sectors.

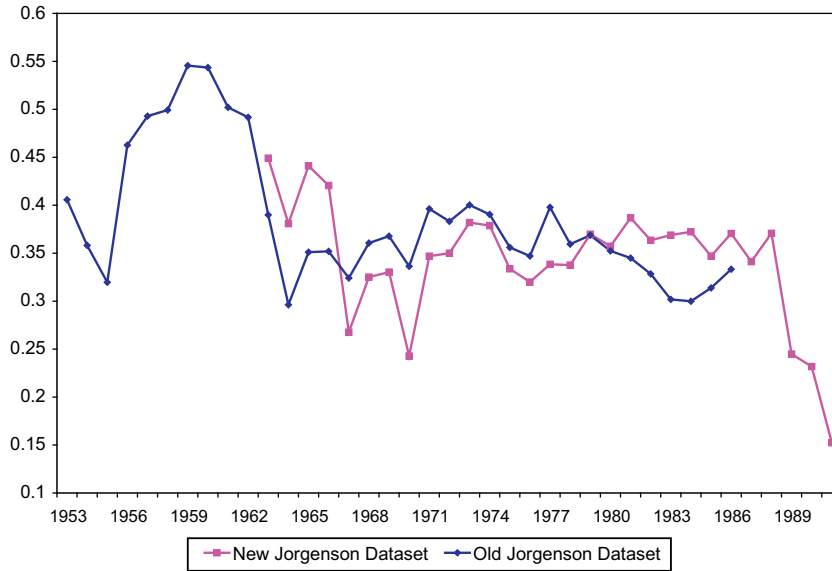


Fig. 7. Evolution of sectoral correlation of productivity growth. Note: Data is from Jorgenson and Stiroh KLEM data sets.

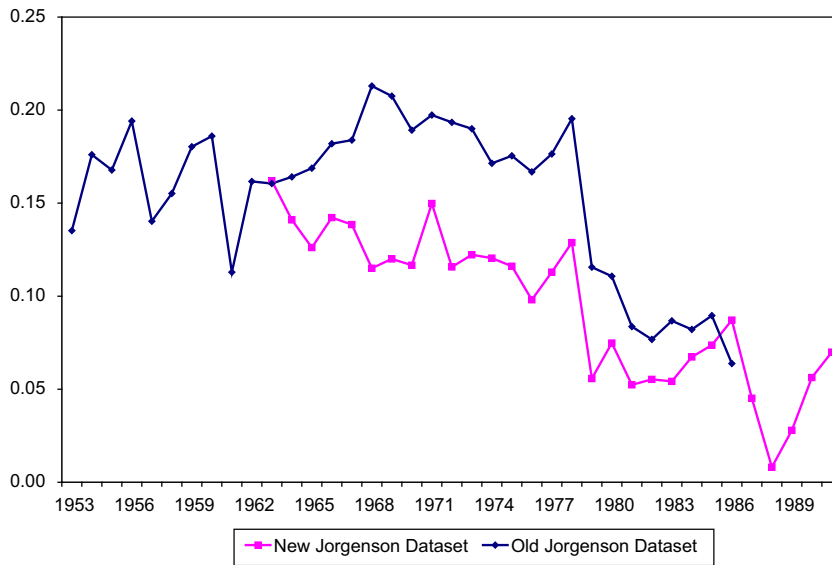


Fig. 8. Correlation of Sectoral TFP Growth. Note: Data is from Jorgenson and Stiroh KLEM data sets.

frequently they adopt the same GIs. Clearly, the probability of such a coincidence is higher for the technologies developed in either of the sector than for technologies developed in other sectors. Specifically, the probability that a technology developed in n (or n') is suitable for adoption in n' (or n) is ψ . The probability that a technology developed in a sector other than n and n' is suitable for adoption in n and n' is $\psi^2 < \psi$. Thus, the covariance between the growth in sectors n and n' is:

$$cov(\gamma_{y_n}, \gamma_{y_{n'}}) = [\psi(\lambda_n^h + \lambda_{n'}^h) + \psi^2(N-2)\bar{\lambda}_{-(n,n')}^h](\ln(\delta_h))^2$$

where $\bar{\lambda}_{-(n,n')}^h$ denotes the average rate of development of general innovations in the sectors other than n and n' . Averaging over all the sectors n' , the average covariance of the growth of sector n with the growth of other sectors is:

$$cov_n = [\psi(\lambda_n^h + \bar{\lambda}_{(-n)}^h) + \psi^2(N-2)\bar{\lambda}_{(-n)}^h](\ln(\delta_h))^2 \tag{29}$$

To explore the cross-section variation in this covariance, suppose, for example, that the efficiency of investments in the development of embodied innovations, $\bar{\lambda}$, varies across sectors. In sectors with higher values of $\bar{\lambda}$, leading firms have fewer incentives to develop GIs. Given the imperfect diffusion of GIs, those sectors with a higher $\bar{\lambda}$ adopt fewer GIs and co-vary less with the rest of the sectors. Hence, there is a negative cross-sectoral relationship between $\bar{\lambda}$ and the average

Table 2
R&D, firm-level volatility and sectoral co-movement.

	Dependent variable											
	Correlation in sectoral productivity growth					Correlation in sectoral TFP growth						
R&D	-3.28 (1.42)		-3.11 (1.44)		-3.39 (1.45)		-2.49 (1.09)		-3.11 (1.06)		-3.1 (1.07)	
Firm level volatility		-0.297 (0.122)		-0.287 (0.121)		-0.27 (0.121)		-0.237 (0.083)		-0.239 (0.084)		-0.25 (0.085)
Energy share			-0.49 (0.37)	-0.35 (0.36)	-0.077 (0.36)	0.076 (0.36)			-0.057 (0.19)	0.065 (0.18)	-0.18 (0.24)	-0.038 (0.22)
N	1011	1011	1011	1011	982	982	1011	1011	1011	1011	982	982
Sectors	All	All	All	All	Non-energy		All	All	All	All	Non-energy	

Notes: Newey-West standard errors are reflected in parentheses.

Firm volatility is measured by the sectoral average of the firm-level variance of the growth rate of sales.

All regressions include sector and year fixed effects.

covariance of a sector. Our previous analysis has also shown that there is a positive relationship between $\bar{\lambda}$ and R&D intensity. Therefore, the model implies a negative cross-sectional relationship between R&D intensity in a given sector and the average covariance of growth in that sector.

Using the same logic as in Section 2.4, it follows that the variance of growth in sector n is:

$$var_n = \lambda_n^q (\ln(\delta_q))^2 + (\lambda_n^h + \psi \bar{\lambda}_{-n}^h) (\ln(\delta_h))^2 \quad (30)$$

The average correlation of growth between sector n and the other sectors, then, is:

$$corr_n = \frac{cov_n}{\sqrt{var_n \bar{var}_{-n}}} \quad (31)$$

where \bar{var}_{-n} is the average variance across sectors other than n . Given the negative effect of $\bar{\lambda}$ on cov_n and the positive effect of $\bar{\lambda}$ on var_n , the model implies a negative cross-sectional relationship between R&D intensity in sector n and the sectoral correlation of growth (expression (31)).

This prediction is very important because it allows us to test (albeit indirectly) the negative effect R&D has on investments in the development of GIs. To test this prediction, we estimate the following specification:

$$corr_{s,t}^{sec} = \alpha_s + \beta t + \gamma RD_{s,t} + \varepsilon_{st} \quad (32)$$

where $corr_{s,t}^{sec}$ is defined in expression (28), and $RD_{s,t}$ denotes the R&D intensity in sector s at time t . The first and seventh columns in Table 2 report the estimate of γ when $corr_{s,t}^{sec}$ is measured by the correlations of productivity and TFP growth, respectively. In both cases, R&D is associated with a significant decline in correlation. Specifically, the estimates of γ are -3.3 for productivity and -2.5 for TFP growth, with p -values of two percent. This implies that the increase in R&D is associated with a decline of between 7.5 and 10 percentage points of the 10 and 25 percentage point decline observed in the sectoral correlation of TFP or productivity growth. These estimates are robust to replacing the time trend with year dummies.

Columns 2 and 8 of Table 2 replace R&D intensity with a sector's firm-level volatility as the explanatory variable. Consistent with the model, higher firm-level volatility in a sector is also associated with lower correlation of sectoral growth with other sectors.³⁶ This shows that the trends in firm and aggregate volatility are not simply a coincidence: A common component can account for an important part of both trends. This is not the case in current models of firm heterogeneity³⁷ because the interactions between firms embedded in these models are not adequate: most of them are partial equilibrium models and treat firms as independent entities. Even though more recent versions of these models have incorporated general equilibrium interactions, they seem insufficient to generate the co-movement patterns that drive the diverging trends in volatility. In this sense, our model emphasizes a particular mechanism that introduces strong interactions between firms and that has aggregate implications for first and second moments of growth.

In principle, the estimated effect of R&D on sectoral correlation could be driven by omitted variable bias. For example, it could be argued that R&D intensity may be related to the sensitivity of sectors to aggregate shocks. However, to the extent that this sensitivity has not changed significantly over time, this effect should be captured by the sector fixed effect. One kind of aggregate shock that has been related to the decline in aggregate volatility is oil price shocks. To test if the omission of the sensitivity of the sector to oil prices is biasing our estimates of γ towards significance, we run regression (32), controlling for the share of energy in the sector. Columns 3, 4, 9 and 10 show that including the share of energy in the control set has no effect on the estimates of the effect of R&D or firm volatility on sectoral correlation. Further, in

³⁶ These results are robust to restricting the sample to private sectors, using other variables to measure firm volatility, using the median instead of the average to measure the firm volatility in the sector, using a measure of turnover in the sector as the independent variable instead of a measure of firm volatility and including a time trend or no trend at all instead of the year fixed effects.

³⁷ For example, Bertola and Caballero (1990) and Gabaix (2005).

Table 3.

Data and model predictions for expected growth rate of productivity at the end of sample ($E\gamma_{y2000}$), initial ($V\gamma_{y1950}$) and final ($V\gamma_{y2000}$) variance of labor productivity.

Moment	Data	Model
$E\gamma_{y2000}$	0.02	0.017
$V\gamma_{y1950}$	$4*10^{-4}$	$2.56*10^{-4}$
$V\gamma_{y2000}$	$1.44*10^{-4}$	$1.44*10^{-4}$
Increment in $V\gamma_y$	$-2.56*10^{-4}$	$-1.12*10^{-4}$

columns 5, 6, 11 and 12, we show that these results hold when we restrict our sample to the sectors other than the energy sector.

Another explanation for the decline in aggregate volatility is proposed by Thesmar and Thoenig (2004). Building on Arrow (1971), they claim that financial innovation can lead to greater risk taking by firms, but also to fewer aggregate credit crunches. Their analysis implies that sectors that benefit more from financial innovation are going to experience larger declines in their correlation with the rest of the economy because of the lower exposure to credit crunches and binding collateral constraints (Bernanke et al., 1996). Lower exposure to financial stress will lead to lower aggregate volatility. Comin and Philippon (2005) empirically explore this hypothesis by including in regression (32) two additional controls that proxy for the degree of financial dependence in the sector: the amount of debt and equity issued in the sector, each divided by the total sales in the sector. In contrast to R&D, both measures of financial market dependence are positively associated with the correlation of sectoral growth (although this relationship is statistically insignificant). Therefore, improvements in financial markets do not seem to be a major force decreasing aggregate volatility. More importantly for our purposes, the negative effect of R&D on the correlation of sectoral growth is not driven by the omission of measures of external financial dependence.

In summary, the existing theories proposed to explain the decline in aggregate volatility do not seem to be driving the negative relationship between R&D and the correlation of sectoral growth. This reinforces the view that, as suggested by our model, this relationship is causal.³⁸

3.6. Calibration

Section 3.3 showed econometric evidence in favor of the model's mechanisms. In what follows, we use a calibration to assess the model's quantitative ability to generate the observed evolutions of aggregate growth and volatility. The lack of independent information on the innovation parameters makes it difficult to conduct a standard calibration. However, the model's ability to account for the evolution of growth and aggregate volatility can be assessed by assuming that the evolution of the correlation of sectoral growth and the market turnover rate are driven by the comparative statics described in Proposition 1. Note that this is a sensible assumption given the econometric results presented in Section 3.3. Using this assumption together with information on the growth rate of aggregate productivity and average variance of sectoral growth in 1950, Appendix 3 shows how we can infer the evolution of the arrival rates of R&D and GIs in 1950 and 2000 together with the parameters δ_h and $\delta_q^{1/N}$. This is all that is needed to determine the model's predictions for the growth rate of productivity in 2000, $E\gamma_{y2000}$, and the variance of aggregate productivity growth in 1950 and 2000 ($V\gamma_{y1950}, V\gamma_{y2000}$). Table 3 shows the actual data as well as the model's predictions for these moments.

This simple exercise illustrates two things. First, the model can account for the lack of a relation between R&D and productivity growth at the aggregate level. Despite the substantial increase in R&D expenses, the model predicts a small decline in expected productivity growth for the year 2000.³⁹ Second, the mechanisms emphasized by the model can account for a significant fraction of the decline in aggregate volatility. The model underpredicts the initial level of aggregate volatility; however, this is not surprising given that the only type of aggregate disturbances are technology shocks, a scenario that is clearly unrealistic. The predicted decline in the variance of aggregate productivity growth, however, represents over 40 percent of the observed decline in aggregate volatility. This estimate must be taken with caution because of the identification assumption that the decline in the co-movement of sectoral growth is entirely driven by the decline in the development of general innovations. However, this assumption may not be far from the truth, given the important negative effects of R&D on sectoral correlation that are estimated above. Moreover, this rough estimate of the contribution of our endogenous technological change mechanisms to the decline in aggregate volatility is consistent with Stock and Watson (2003)'s conclusion: after considering the effects of a more active monetary policy and lower commodity price shocks, 50 percent of the decline in aggregate volatility must be due to less volatile technology shocks.

³⁸ Philippon (2003) argues that an increase in competition in the goods market leads firms to adjust their prices faster, which reduces the impact of aggregate demand shocks. While intuitively appealing, Philippon (2003)'s is a within-sector explanation with no implication for the evolution of sectoral co-movement.

³⁹ This calibration implies that about 90 percent of aggregate productivity growth was driven by general innovations in 1950. This fraction declined to 67 percent by 2000.

4. Conclusion

This paper has presented an explanation for why R&D and growth are uncorrelated within countries and sectors and across countries but are strongly correlated at the firm level. The key to this theory consists in modelling the development of general innovations, which differ from standard innovations in their limited appropriability and their generality. We have shown that there are interesting interactions between these two types of innovations. In particular, the Schumpeterian dynamics associated with R&D innovations reduce the leaders' incentives to develop GIs. As a result, R&D subsidies lead to a negative co-movement in the development of these two types of innovations. This equilibrium result allows us to rationalize the varying relationship between R&D and growth at different aggregation levels.

This paper has also brought attention to the importance of second moments of the growth process to test growth models. The endogenous growth literature has ignored the model's implications for the second moments of the growth process, as if their determinants were orthogonal to the first moments' determinants. Comin and Philippon (2005) and this paper find, however, that there is a significant association between R&D investments and both firm and aggregate volatility. In particular, it has showed (i) that firm volatility and market turnover are positively associated with R&D; (ii) that R&D subsidies and aggregate volatility are negatively associated across countries, and (iii) that sectors with higher increases in R&D have also experienced greater declines in the correlation of their growth with the rest of the economy. These findings have interesting implications. First, they provide evidence of the connection between the first and second moments of the growth process. Second, they support the view that this connection operates mainly through the effect of R&D on the decline in the co-movement of growth across sectors. By no means does this imply that all of the decline in aggregate volatility (or increase in firm volatility) is driven by this common component associated with R&D. However, it does show that this component is an important piece of the puzzle.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at [10.1016/j.jmoneco.2009.10.004](https://doi.org/10.1016/j.jmoneco.2009.10.004).

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