Innovations and Market Value of Firms: Differential Effects of Leaders and Followers

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Abstract

We use a latent-factor patent count data model and a panel VAR model in order to analyze the lagged impact of observable and latent determinants of patent activity on the stock market value and patent activity of competitors for six industries – aircrafts, pharmaceuticals, computers, software, defense and oil sectors – in the U.S. during 1979-2000. We identify R&D leader and follower companies in each sector using alternative definitions. We find that the relative importance of the latent patent intensity component has increased in the pharmaceuticals, computers, software and defense sectors. We also find that the latent component has decreased in the aircrafts and oil industries. Regarding the observable patent intensity component, we find that it has increased in all sectors. Moreover, we evidence that R&D leader and follower firms have had significant and different influence on the market value and patent activity of competitors in each sector analyzed.

JEL classification: C15; C31; C32; C33; C41

Keywords: Competitve diffusion; R&D spillovers; Stock market value; Patents; Conditional intensity

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1. Introduction

In the R&D literature, a question that has generated long debates is how monopoly rights (patents, etc.) and competition affect innovation and productivity growth.[1] There are two clear opposite views: Innovation under competition reduces *innovations rents*, relative to the monopoly rents, but innovation is also a mechanism to escape competition (*competitive advantage*) and in that sense increases *innovation rents*. These two opposite views are also express as follows: First, a "*rent dissipation effect of competition*" which says that tough competition *discourage innovation* and productivity growth by reducing the expected rents from innovation. By reducing the monopoly rents, competition discourage firms from doing R&D activities which lower the innovation rate and the long run growth. The initial endogenous growth models of technical change of Romer (1990), Aghion and Howitt (1992), Grossman and Helpman (1991), predict that competition (or the imitation rate) has a negative effect on entry and innovation and therefore on productivity growth. That is, patent protection protects monopoly rents from innovation, enhancing further innovation and growth (Schumpeterian view). Second, the "*escape competition effect*", followed by most competition authorities, says that competition is a necessary input for innovation both because it encourages new entry and because it *forces incumbent firms to innovate* and reduce costs to survive and therefore is productivity and growth enhancing. Which of the two competition effects dominate is an empirical question. For example, Crépon et al (1998) study the relationship between productivity, innovation and research at the firm level using a structural model. In particular, they find that firm innovation output raises with research effort and other indicators through theirs effects on research and that firm productivity correlates positively with innovation output (patents). Aghion et al (2003) estimate an inverted-U relationship between innovation (citation-weighted patent count) and product market competition which is steeper for more neck-to-neck industries.

In a recent empirical application, Blazsek and Escribano (2010) also obtain an inverted-U relationship between R&D (after controlling for patent citations) and innovation (measured by patent application counts). They introduce new methods to control for firm-level observed and unobserved R&D spillovers in the U.S. economy over a long period of 22 years (1979-2000) merging patent data form MicroPatents and from the NBER data files. They consider latent R&D spillovers in their model because previous R&D literature realized that knowledge spillovers are partly observable and partly latent but they were only able to control for observable spillovers. Hall et al (2001) suggest using patent citation data, which is fully available for a very long time period for all U.S. firms, to measure observable knowledge spillovers with the citations published in patent documents. By extending the latent-factor intensity approach of Bauwens and Hautsch (2006) to dynamic patent count data models, Blazsek and Escribano (2010) are able to identify unobserved knowledge flows among several companies. Another important contribution of their approach is that they explicitly allow for cross-sectional dependence (co-movements) in the panel data model through the common unobserved stock of knowledge. Therefore, the dynamic count data model with unobservable innovation components of Blazsek and Escribano (2010) is an extension of the canonical count data model of patent applications

[1] Aghion and Griffith (2005) provide an interesting overview.

of Hausman et al (1984) and of more recent contributions by Blundell et al (2002) and Wooldridge (2005).

Present paper builds on the methodology and results obtained by Blazsek and Escribano (2010). We use their patent count panel data framework that includes dynamic latent variables in order to analyze the impact of observable and unobservable patent activity on own and competitors' stock returns and patent intensity. The model is capable to separate observable and latent innovations and analyze the impact of each component on own and competitors' market value and patent activity. In this paper, we employ a large U.S. data set covering a 22-year time period between 1979 and 2000 for some industries, identify R&D leader and follower companies using alternative definitions and analyze the evolution of stock market returns related to various forms of patent intensity. During the past two decades, innovations protected by patents have played a key role in business strategies. This fact motivated several studies of the determinants of patents and the impact of patents on innovation and competitive advantage. Patents help sustaining competivite advantages by increasing the production cost of competitors, by signaling a better quality of products and by serving as barriers to entry. Griliches (1990) states that the main advantages of patent data are the followings: (a) by definition patents are closely related to inventive activity; (b) patent documents are objective because they are produced by an independent patent office and their standards change slowly over time; and (c) patent data are widely available in several countries, over long periods of time, and cover almost every field of innovation.

If patents are rewards for innovation, more R&D should be reflected in more patents applications but this is not the end of the story. There is empirical evidence showing that patents through time are becoming easier to get and more valuable to the firm due to increasing damage awards from infringers. Shapiro (2007) notes that patents are playing an increasingly important, and shifting, role in the US. There is evidence that firms in a number of industries adjusted their strategies in the 1980s and early 1990s in response to changes in the patent system: they began seeking more patents, but not because they were devoting more resources to R&D (Shapiro, 2007). Innovation activity exists because it has a positive impact on future profits of a company, which motivates owners to promote innovative activity within their firm. Since profits on R&D are usually realized during several years in the future, current accounting-based net profit is a very noisy measure of R&D benefits. Therefore, in the economics literature, several papers have decided to investigate the impact of R&D on stock market price, which avoids the problem of timing differential of R&D expenses and associated future profits by a forward-looking perspective. In addition, this approach is also useful for the consideration of various measures of R&D activity that may capture econometrically observable and latent innovations like for example patents and trade secrets, respectively, because investors may be aware of R&D related information hidden from the researcher. Griliches (1981) constructs a stock of knowledge variable from lagged R&D expenses and number of patents. He finds significant positive relationship between market value and R&D expenditure and number of patents for a panel of large U.S. firms for 1968-1974. Pakes (1985) focuses on the dynamic relationships among the number of successful patent applications of firms, a measure of the firm's investment in inventive activity (its R&D expenditures), and an indicator of its inventive output (the stock market value of the firm). Pakes concludes that the events that lead the market to reevaluate the firm are significantly correlated with unpredictable changes in both the R&D and the patents of the firm. Hall (1993) investigates the relationship between R&D and market value of U.S. manufacturing firms between 1976 and 1991. Hall (1993) evidences that stock market valuation of R&D broke down in the mid-80s. From the second half of the 80s, R&D is much less valued than before.[2] Nevertheless, a number of studies have shown the correlation of R&D activity with contemporaneous and future market value. Lev and Sougiannis (1996) estimate the inter-temporal relation between the R&D capital and subsequent stock returns of public firms in the U.S. during 1975-1991.[3] Blundell et al (1999) use U.S. firm-level panel data for 1972-1982. They study the relationship between innovations and market value. They employ a dynamic panel count data model to model innovative activity and a market value model to estimate the relationship between the firm's stock of innovations and its stock market value.[4] The authors examine the relationship between *surprise innovations* (difference between predicted number of innovations and actual number) and firm performance. They find a positive impact of innovation on market value. Chan et al (2001) investigate the relationship between R&D capital and stock returns of U.S. firms for 1975-1995. They define R&D capital based on the estimates of Lev and Sougiannis (1996) as a weighted sum of contemporaneous and four lags of R&D expenses. Chan et al (2001) show a positive relationship between R&D intensity as measured by R&D to market value and abnormal future returns.[5] Moreover, the authors also show that the future excess returns for R&D intensive firms are driven by lower stock price valuation in the current year due to R&D firm's earnings being depressed. Hall et al (2005) investigate the relation between knowledge stock and market value in the U.S. during 1963-1995.[6] Their results show that patent citations contain important information about stock market value in addition to patent counts. Recently, some researchers have investigated the market value-R&D interaction for European data as well. Hall and Oriani (2006) investigate R&D and market value for German, French and Italian data. Moreover, Hall et al (2007) analyze the same issue in 33 European countries. These authors find mixed, country-dependent results regarding the market valuation of R&D activity.

Technological improvement gives the innovators a competitive advantage. However, the non-rival nature of knowledge creates a business-stealing (competitive) effect by decreasing the cost of subsequent own innovations. A spillover of knowledge occurs when a new innovation created by a technological

[2]Hall et al (2006) also show that the valuation on R&D has been relatively low during the 90s.

[3]First, they estimate the relation between R&D expenses and subsequent earnings to compute firm specific R&D capital and its amortization rate. Second, they adjust reported earnings and books for R&D capital and show that the adjusted values are significantly related to contemporaneous stock valuation. Third, they show that R&D capital, defined as weighted sum of past R&D expenses, is associated with subsequent stock returns. See also Lev et al (2005).

[4]The stock of innovation variable is constructed from a count of "technologically significant and commercially important" innovations commercialized by the firm (i.e., not only from patent counts).

[5]This association of R&D activity and future excess stock returns could be due to delayed reaction by the stock market or inadequate adjustment for risk (see Chambers et al, 2002). Chambers et al (2002) estimate the relationship between R&D and stock valuation of U.S. firms during 1979-1998. They define R&D in the same way as Chan et al (2001) and they find positive relationship between R&D and stock returns.

[6]The knowledge stock variable is constructed from R&D expenses, number of patents and citations information to capture the importance of patents. They build on Griliches (1981) and estimate Tobin's q equations. In the market value equation they use (1) R&D/assets, (2) Patents/R&D, (3) Citations/patents, (4) Self-citations/patents, (5) Self-citations/total citations as measures of R&D.

leader firm is adopted by another (follower) firm. In the economic literature, many researchers have analyzed knowledge spillovers. Scherer (1981) constructs an inter-industry technology flows matrix to measure knowledge spillovers between industries. Jaffe (1986) finds evidence of R&D spillovers using various indicators of R&D activity. He evidences that firms whose research is in a sector where there is high research intensity in general obtain more patents per dollar of R&D, and a higher return to R&D in terms of accounting profits or market value, though firms with low own R&D have lower profits and market value if their neighbors are R&D intensive. Jaffe (1988) classifies firms into different technological clusters to identify the proximity of firms in the technology space. Harhoff et al (1999) combine German and U.S. patent value survey and backward citation data. They find that patents reported to be relatively more valuable by the companies holding them are more heavily cited in subsequent patents. Jaffe et al (2000) survey R&D managers in order to validate the use of patent citations to approximate the unobservable process of knowledge transfer. Lanjouw and Schankerman (1999) and Hall et al (2001) validate the use of patent statistics in economic research. They suggest that the intensity of forward citations (the number of citations received from subsequent patents) can be used to measure the significance of innovations, while backward citations (citations made to previous patents) can be used to capture R&D spillovers. Fung and Chow (2002) look at potential knowledge pools at the industrial level. Fung (2005) uses patent citations data to analyze the impact of knowledge spillovers on the convergence of productivity among firms. In a recent paper, Lev et al (2006) use U.S. data on the 1975-2002 period. They differentiate between R&D leaders and followers and compare the stock market valuation of R&D leaders and followers. They show that R&D leaders earn significant future excess returns, while R&D followers only earn average returns. Lev et al (2006) find that R&D leaders show higher future profitability and lower risk than followers, but the investors' reaction seems to be delayed. They conclude that investors probably do not get information in a timely fashion leading to a delayed reaction.

In summary, previous R&D papers on market value and R&S spillovers motivate us to model patent intensity and stock market value in dynamic setup and also to use a multivariate model to identify R&D leader and follower companies, where observable and latent R&D spillovers are captured. Therefore, we use the methodology of Blazsek and Escribano (2010) and assume that firms' patent intensity, λ_{it} includes the following two components: (a) observable patent intensity λ_{it}^{o} and (b) latent patent intensity λ_{it}^{*}.

Remaining part of the paper is structured as follows. First, we introduce the econometric model in Section 2. Then, Section 3 discusses the estimation method. Section 4 describes the patent and firm specific data applied. Section 5 summarizes our empirical results. Finally, Section 6 concludes.

2. The model

The econometric model is presented in three subsections. First, we present the dynamic market value model that relates own and leaders' observable and unobservable patent intensity to the firm's stock market value in Section 2.1. Second, we clarify the definition of R&D leadership and relate it to previous economic and strategic management literature in Section 2.2. Finally, we overview the dynamic patent count data model applied that separates observable and latent determinants of patent intensity in

Section 2.3.

2.1. Market value – the panel vector autoregression model

In order to analyze the dynamic interaction between patent activity and stock market value, we propose a panel vector autoregression (PVAR) specification where we are model the intra-firm and inter-firm dynamic interaction between patent intensity and stock return in the industry and also account for the impact of stock market return. We use an extension of the PVAR(1) model of Binder et al (2005) to model stock returns y_{it} and patent intensity λ_{it} of $i = 1, \ldots, N$ firms over $t = 1, \ldots, T$ periods.[7] We decompose λ_{it} into the product of several components that include an observable intensity component, λ_{it}^{o} and a latent intensity component, λ_{it}^{*}. We measure the dynamic within firm and between firm interaction among (a) stock return y_{it}, (b) log observable patent intensity $\ln \lambda_{it}^{o}$ and (c) log latent patent intensity $\ln \lambda_{it}^{*}$ using a PVAR model that includes exogenous variables (PVAR-X model). Define the 3×1 vector for the variables of firm i and period t by $X_{it} = (x_{1it}, x_{2it}, x_{3it})' = (y_{it}, \ln \lambda_{it}^{o}, \ln \lambda_{it}^{*})'$. Moreover, let $\overline{y}_t$ denote the stock market return in period t and let D_{Lit} denote a dummy variable indicating R&D leadership defined as:

$$D_{Lit} = \begin{cases} 1 & \text{if firm } i \text{ is an R\&D leader in year } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

In section 2.2, we provide alternative and more precise definitions of R&D leadership.

Assumption 1 (exogeneity). Suppose that $\overline{y}_t$, past values of R&D leader firms' observable and latent patent intensity components and D_{Lit} are exogenous variables in period t.

Let $\tilde{X}_{it} = (\tilde{x}_{1it}, \tilde{x}_{2it}, \tilde{x}_{3it})'$ be the following transformation of endogenous variables with respect to the exogenous variables:

$$\begin{pmatrix} \tilde{x}_{1it} \\ \tilde{x}_{2it} \\ \tilde{x}_{3it} \end{pmatrix} = \begin{pmatrix} x_{1it} \\ x_{2it} \\ x_{3it} \end{pmatrix} - \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \overline{y}_t - \sum_{j \neq i} \sum_{k=1}^{p} \begin{pmatrix} 0 & \zeta_{Lk12} & \zeta_{Lk13} \\ 0 & \zeta_{Lk22} & \zeta_{Lk23} \\ 0 & \zeta_{Lk32} & \zeta_{Lk33} \end{pmatrix} \begin{pmatrix} x_{1jt-k} \\ x_{2jt-k} \\ x_{3jt-k} \end{pmatrix} D_{Ljt}, \tag{2}$$

where the $\beta = (\beta_1, \beta_2, \beta_3)'$ vector measures the impact of the stock market return $\overline{y}_t$ on the firm's stock return and patent intensity. The ζ_{Lk} 3×3 matrix measures the impact of the k-th lag of the sector's R&D leader company on $\tilde{X}_{it}$.[8] In the PVAR-X model, a particular element of the $\tilde{X}_{it}$ vector has the following form:

$$\begin{pmatrix} \tilde{x}_{1it} \\ \tilde{x}_{2it} \\ \tilde{x}_{3it} \end{pmatrix} = \begin{pmatrix} a_{i1} \\ a_{i2} \\ a_{i3} \end{pmatrix} + \begin{pmatrix} \zeta_{11} & \zeta_{12} & \zeta_{13} \\ \zeta_{21} & \zeta_{22} & \zeta_{23} \\ \zeta_{31} & \zeta_{32} & \zeta_{33} \end{pmatrix} \begin{pmatrix} \tilde{x}_{1it-1} \\ \tilde{x}_{2it-1} \\ \tilde{x}_{3it-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{it1} \\ \epsilon_{it2} \\ \epsilon_{it3} \end{pmatrix}, \tag{3}$$

[7] We extend Binder et al (2005) at least in two aspects: First, we consider exogenous variables in the PVAR equation: stock market return and patent intensity components of R&D leaders. Second, we measure the lagged interaction between different individuals in the panel.

[8] The ζ_{Lk} matrix of parameters is identical to all leader firms if there were several R&D leader companies. Notice that the first column of ζ_{Lk} is restricted to zero values. We impose this restriction in order to reduce the number of parameters in the PVAR model. Moreover, in the empirical part of this paper we report results corresponding to the $k = 1$ specification to reduce the number of coefficients to be estimated.

where $a_i = (a_{1i}, a_{2i}, a_{3i})'$ is a 3×1 vector of firm specific *random effects* with covariance matrix Ω_a.[9] The ζ is a 3×3 matrix capturing the dynamic impact of the first lag of own stock return, observable and latent patent activity on current own stock return and patent activity. The PVAR(1) model is covariance stationary if all eigenvalues of ζ are inside the unit circle. We control for the initial conditions $\tilde{X}_{i0}$ by introducing the Ω_0 covariance matrix of $\tilde{X}_{i0}$ in order to apply the model is a short-panel setup. Moreover, $\epsilon_{it} \sim N(0, \Omega_\epsilon)$ is a vector of error terms where Ω_ϵ is a 3×3 covariance matrix of the error terms capturing the contemporaneous interaction of various forms of patent intensity and stock returns. Elements of the ϵ_{it} vector of error terms may be contemporaneously correlated with each other (through Ω_ϵ) but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables of the regression equation. Finally, we may rewrite the PVAR-X model using a more compact matrix notation as follows:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon) \tag{4}$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \sum_{k=1}^{p} \zeta_{Lk} X_{jt-k} D_{Ljt}. \tag{5}$$

2.2. Leader-follower definitions

The relationship between stock market value and R&D of firms is investigated by recognizing that R&D activities are different among companies. Firms strategically decide to be R&D leaders or followers (see Porter, 1979, 1980, 1985). Some companies are R&D leaders who introduce innovative products while others are followers who mimic the products of the leaders. Results in the strategic management and in the economics literature suggests that R&D leaders have sustained future profitability. Thus, the nature and focus of R&D efforts could be different across firms from a strategic point of view.

Research in economics provides insights into the interactions between strategy, competition and R&D activities. Caves and Porter (1977) introduce a framework that explains intra-industry profit differentials based on pre-commitment to specialized resources such as R&D. Caves and Ghemawat (1992) investigate the factors that sustain profit differences across firms within an industry and find that differentiation-related strategies which includes R&D, are more important than cost-related strategies. They find that differentiation related strategies are indicative of research leadership in the product market by introducing new products, services, brands, etc. while cost-related strategies include higher capacity and cost structure advantages. Klette (1996) shows that R&D activities may improve future profitability due to knowledge spillovers across business lines. In summary, the evidence on interaction between business strategy, competition and innovation suggests that R&D leadership provides sustained future performance through a combination of (a) provision of differentiated products, (b) economies of scope and (c) knowledge spillovers.

[9] An alternative choice for unobservable heterogeneity could be the *fixed effects* specification also discussed in Binder et at (2005). In our application, we also estimated the PVAR model with *fixed effects* and have found similar results to the *random effects* model. Therefore, in this paper we only report the PVAR with *random effects* estimation results.

The strategic management literature makes a clear distinction between R&D leaders and followers. Reinganum (1985) shows that incumbent firms have less incentives to invest in innovation and therefore entrants overtake incumbents, even though incumbents make more profits in the short-term entrants are more profitable in the long-term. On the other hand, Gilbert and Newbery (1982) analyze a model where incremental innovations are awarded to the firm that spends the most on R&D and show that the incumbent firm continues to earn monopoly rents. Jovanovic and MacDonald (1994) point out that innovation and imitation tend to be substitutes. Though, the benefits generated by spillovers depend on the technological differences among firms and the absorptive capacity of the imitator firm. Naturally, these factors create time lags in the adoption of technologies. For example, Nabseth and Ray (1974) and Rogers (1983) report that it may take a decade for some firms to adopt an innovation developed by others. Mansfield et al (1981) and Pakes and Schankerman (1984) also suggest that knowledge 'spills over' gradually, in a dynamic fashion to competitors.

Based on the insights from existing literature, we classify R&D leaders and followers by R&D impact: Firms with R&D impact greater than (lesser than) that of competitors are classified as leaders (followers). We propose three definitions of R&D leadership (definitions 1-3) and for each of them we consider alternatives (a), (b) or (c).

Definition 1(a): $$\text{R\&D leader} = \arg\max_i \left\{ \sum_{t=1}^{T} n_{it} : i = 1, \ldots, N \right\}, \tag{6}$$

where n_{it} denotes the number of patent applications.

Definition 1(b): $$\text{R\&D leader} = \arg\max_i \left\{ \sum_{t=1}^{T} \tilde{c}_{it} : i = 1, \ldots, N \right\}, \tag{7}$$

where $\tilde{c}_{it}$ is the number of patent citations received from future patents.[10]

Definition 1(c): $$\text{R\&D leader} = \arg\max_i \left\{ \sum_{t=1}^{T} \omega_{it} n_{it} : i = 1, \ldots, N \right\}, \tag{8}$$

where $\omega_{it} n_{it}$ with $\omega_{it} = \tilde{c}_{it} / \sum_{k=1}^{T} \tilde{c}_{ik}$ denotes the number of patent applications weighted by the number of citations received. Table 1 presents the ranking of firms for each sector to identify the R&D leader firms according to definition 1. Furthermore, Table 1 also presents a classification of firms into three groups in each industry. The following definition 2 is based on this classification. (See Table 1 in Section 5.)

Definition 2(a)(b)(c): Firm i is an R&D leader over $1 \leq t \leq T$ if it belongs to the first two groups of the ranking of Table 1.

Notice that R&D leadership does not change according to previous definitions. The next definition 3 does not imply constant R&D leadership. In definition 3, firms are assumed to accumulate a knowledge

[10] The tilde notation in $\tilde{c}_{it}$ refers to the fact that the number of citations received from future patents is corrected for sample truncation bias using the *fixed effects* approach of Hall et al (2001). See in Section 4.3 for further details.

stock over $1 \leq t \leq T$. This stock of knowledge is built up using information about past patents applications and/or and citations received counts for each firm. In order to account for the decreasing value of past knowledge in the knowledge stock, we use a depreciation rate δ in the following formulas:

$$\textit{Definition 3(a):} \qquad \text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is}(1-\delta)^{(t-1)-s} : i = 1,\dots,N \right\} \tag{9}$$

$$\textit{Definition 3(b):} \qquad \text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is}(1-\delta)^{(t-1)-s} : i = 1,\dots,N \right\} \tag{10}$$

$$\textit{Definition 3(c):} \qquad \text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is} n_{is}(1-\delta)^{(t-1)-s} : i = 1,\dots,N \right\} \tag{11}$$

According to definition 3, R&D leadership may change over time. See Table 3 to identify R&D leader firms during 1979-2000 for each industry.[11] (See Table 3 in Section 5.)

2.3. Patent intensity – the latent-factor Poisson model

In the first part of this subsection, we introduce the mathematical notation required for the definition of the dynamic patent count data model that includes observable and latent variables. Then, we present the latent-factor Poisson (LFP) model of patent intensity suggested by Blazsek and Escribano (2010) for $i = 1,\dots,N$ firms and $t = 1,\dots,T$ periods.

Denote n_{it} the number of patent applications. Denote the set of patent counts by $N_{ij} = \{n_{it} : t = 1,\dots,j\}$ with $1 \leq j \leq T$. Let r_{it} denote log-R&D expenditure and let $r_t = (r_{1t},\dots,r_{Nt})'$. Let $c_{it} = (c_{1it}, c_{2it})'$ denote a 2×1 vector capturing observable R&D spillovers. The elements of c_{it} represent two components of the spillover of knowledge from two knowledge pools (see Fung, 2005): (1) intra-industry knowledge pool: knowledge produced by other firms in the same industry, c_{1it}; and (2) inter-industry knowledge pool: knowledge produced in other industries, c_{2it}. Let $c_t = (c_{1t},\dots,c_{Nt})'$. Moreover, let Ω denote the $3N \times T$ data matrix of R&D expenses and patent citations:

$$\Omega = \begin{pmatrix} \Omega_1 & \cdots & \Omega_T \end{pmatrix} = \begin{pmatrix} r_1 & r_2 & \cdots & r_T \\ c_1 & c_2 & \cdots & c_T \end{pmatrix}. \tag{12}$$

Let $Q_j = \{\Omega_t : t = 1,\dots,j\}$ with $1 \leq j \leq T$. Finally, let l_t^* denote the value of a latent variable in the t-th period, interpreted as common unobservable innovations. Denote the set of latent variables by $L_j^* = \{l_t^* : t = 1,\dots,j\}$ with $1 \leq j \leq T$.

Similarly to Hausman et al (1984), the patent application intensity of firms is modeled by specifying the conditional hazard function of the point process formed by the patent arrival times. Define the conditional hazard function at instant $\tau \geq 0$ corresponding to the firm i in the period t as follows (see Cox and Isham, 1980):

$$\lambda_{it}(\tau) = \lim_{\delta_0 \to 0} \frac{\Pr\{n_{it}(\tau + \delta_0) - n_{it}(\tau) > 0 | N_{it-1}, L_t^*, Q_t\}}{\delta_0}, \tag{13}$$

[11] In the R&D literature it is accepted to choose $\delta = 15\%$. See for example Hall (1993) and Hall et al (2005). Therefore, we employ the $\delta = 15\%$ discount rate in this paper. We compute the knowledge stock until time $t-1$ because n_{it} is an endogenous variable in our model.

where $\delta_0 > 0$ and $n_{it}(\tau)$ is the number of patents of the firm i until instant τ in the period t.[12] In the remaining part of this paper, the conditional hazard is assumed to be constant during each period, therefore, it can be indexed by t as follows: $\lambda_{it} = \lambda_{it}(\tau)$. The λ_{it} can be interpreted as the instantaneous probability that firm i has a new patent at any point of time of period t given all information available in the beginning of period t. Thus, the conditional hazard, λ_{it} represents the patent application intensity of firm i in period t. Since the conditional hazard is assumed to be constant during each period, the statistical inference of the model can be done based on the number of patents occurred in each time interval. Moreover, the conditional distribution of patent counts in each period is a Poisson distribution with parameter λ_{it} due to the constant intensity assumption.

The patent intensity model in this paper is an application of the panel data model of Blazsek and Escribano (2010). The patent application intensity $\lambda_{it} = E[n_{it}|N_{it-1}, L_t^*, Q_t]$ is formulated as follows:

$$\ln \lambda_{it} = \mu_{0i} + \ln \lambda_{it}^o + \ln \lambda_{it}^*, \tag{14}$$

where μ_{0i} is a constant parameter capturing firm specific latent characteristics (*fixed effects*), λ_{it}^o represents the observable component of patent intensity and λ_{it}^* denotes the latent component of patent intensity. The observable intensity component, λ_{it}^o is given by

$$\ln \lambda_{it}^o = \kappa_0 n_{i1} + \kappa_1 \ln \lambda_{it-1}^o + \gamma_1 r_{it} + \gamma_2 r_{it}^2 + \phi_1 c_{1it} r_{it} + \phi_2 c_{2it} r_{it}, \tag{15}$$

where κ_0 controls for initial conditions and $|\kappa_1| < 1$ measures the AR(1) impact of the observable component.[13] The γ_1 captures the impact of R&D expenses and γ_2 controls for the non-linearities of R&D expenses, Moreover, ϕ_1 and ϕ_2 measure the interaction of R&D expenses with intra-industry and inter-industry patent citations, respectively. The latent patent intensity component, λ_{it}^* captures unobserved innovations and is specified as follows:

$$\begin{aligned} &\ln \lambda_t^* = \sigma_i l_t^* \\ &l_t^* = \mu l_{t-1}^* + u_t \\ &u_t \sim N(0,1) \text{ i.i.d}, \end{aligned} \tag{16}$$

where $|\mu| < 1$ captures the dynamics of latent patent intensity and σ_i is a real parameter that measures the impact of l_t^* on patent intensity.[14] This specification allows us to separate observable and latent patent intensity and also to study the dynamics of observable and latent determinants of the patent applications intensity process.

[12] Notice that we condition on r_t, c_t and l_t^* in the conditional intensity in period t. Thus, R&D expenses and patent citations are exogenous variables in our patent count data model. Blazsek and Escribano (2010) show that the latent variable l_t^* may help to solve the potential endogeneity problem of R&D expenses reported by previous authors of the R&D literature.

[13] This specification is different from Wooldridge (2005) because he considers the n_{it-1} dynamic term in his model of λ_{it}. In our model, n_{it} includes both the observable and latent components by construction. Therefore, we do not include the n_{it-1} term directly into λ_{it}^o or λ_{it}^*. Instead, we include λ_{it-1}^o into λ_{it}^o because this way we can separate the observable and latent components of patent intensity.

[14] Notice that in the AR(1) specification of equation (16), we restrict the constant to zero value due to identification reasons.

3. Inference

In this section, some details of the estimation procedure are presented. The statistical inference of the econometric models presented in the previous section is performed in three steps. In Section 3.1., we present the estimation of the parameters of the LFP patent intensity model using the efficient importance sampling (EIS) technique.[15] In Section 3.2, we discuss the computation of the expected value of the latent intensity component conditional on the observable information set. In Section 3.3, we estimate the stock market value PVAR-X models using the estimated observable and latent patent intensity and the stock return time series.

3.1. Latent-factor Poisson model

The latent-factor patent count model is estimated by maximum simulated likelihood (MSL) method (see Gouriéroux and Monfort, 1991). First, denote the conditional Poisson density of $n_{it}|(N_{it-1}, L_t^*, Q_t)$ as follows:

$$f_t(n_{it}|N_{it-1}, L_t^*, Q_t) = \frac{\exp(-\lambda_{it})\lambda_{it}^{n_{it}}}{n_{it}!}. \tag{17}$$

Notice that the λ_{it} intensity is conditional on l_t^*. Second, denote the density of the latent factor l_t^* conditional on l_{t-1}^* as follows:

$$f_t^*(l_t^*|l_{t-1}^*) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(l_t^* - \mu l_{t-1}^*)^2}{2}\right). \tag{18}$$

If all latent variables l_t^* were observable then the joint likelihood of a realization $\{n_{it}, l_t^* : i = 1, \ldots, N; t = 1, \ldots, T\}$ could be written as the product of $f_t(n_{it}|N_{it-1}, L_t^*, Q_t)$ and $f_t^*(l_t^*|l_{t-1}^*)$ as follows:

$$\prod_{t=1}^{T}\prod_{i=1}^{N} f_t(n_{it}|N_{it-1}, L_t^*, Q_t) f_t^*(l_t^*|l_{t-1}^*) = \prod_{t=1}^{T}\prod_{i=1}^{N} \frac{\exp(-\lambda_{it})\lambda_{it}^{n_{it}}}{n_{it}!} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(l_t^* - \mu l_{t-1}^*)^2}{2}\right). \tag{19}$$

However, the $L_T^* = \{l_t^* : t = 1, \ldots, T\}$ are not observed. Therefore, we integrate out all latent variables from the likelihood function with respect to the assumed normal distribution to get the marginal density of patent counts. Since the number of l_t^* is equal to the number of periods T, the integrated likelihood function is the following T-dimensional integral:

$$\mathcal{L} = \int_{\mathbb{R}^T} \prod_{t=1}^{T}\prod_{i=1}^{N} f_t(n_{it}|N_{it-1}, L_t^*, Q_t) f_t^*(l_t^*|l_{t-1}^*) dL_T^* = \int_{\mathbb{R}^T} \prod_{t=1}^{T}\prod_{i=1}^{N} g_t(n_{it}, l_t^*|N_{it-1}, L_{t-1}^*, Q_t) dL_T^*, \tag{20}$$

where g_t denotes the joint density of (n_{it}, l_t^*). The major difficulty related to the statistical inference of the model is the precise evaluation of the T-dimensional integral in $\mathcal{L}$ for given parameter values.

[15] We note that estimation of the patent intensity model is computation intensive, therefore, it is feasible to estimate that model only for a limited number of firms or to consider a univariate patent intensity model. In our empirical application, we restrict our attention to univariate LFP models. Nevertheless, we present the estimation procedure for an arbitrary number of firms. See more details of the statistical inference of the LFP model in Blazsek and Escribano (2010).

This is performed numerically by the EIS method of Richard and Zhang (2007). The EIS technique is presented in details in Appendix 1.

3.2. Filtered estimates of latent patent intensity

Before estimating the PVAR-X equation, we need to compute the conditional expectation of the latent patent activity component given the observable information set, i.e. $\lambda_{it}^* \equiv E[\lambda_{it}^*|N_{it-1}, Q_t]$. In order to obtain this estimate, we need to integrate out all latent variables l_t^* from the expectation and the conditional expectation can be computed similarly to Bauwens and Hautsch (2006, pp.460) as follows:

$$\lambda_{it}^* \equiv E[\lambda_{it}^*|N_{it-1}, Q_t] = \frac{\int_{\mathbb{R}^t} \lambda_{it}^* f_t^*(l_t^*|l_{t-1}^*) g(N_{it-1}, L_{t-1}^*|Q_{t-1}, \theta_t) dL_t^*}{\int_{\mathbb{R}^{t-1}} g(N_{it-1}, L_{t-1}^*|Q_{t-1}, \theta_t) dL_{t-1}^*}, \tag{21}$$

where g is the joint density of (N_{it-1}, L_{t-1}^*) conditional on Q_{t-1}. The high-dimensional integrals in this ratio cannot be computed analytically but can be approximated numerically by the EIS technique presented in Appendix 1. Then, λ_{it}^* can be included into the PVAR equation to estimate the contemporaneous and lagged impact of leaders' observable and latent patent activity on competitors' stock returns and patent intensity.

3.3. The PVAR-X model

We apply the quasi maximum likelihood (QML) method suggested by Binder et al (2005) to estimate the PVAR-X model with random effects.[16] We extend the methodology of Binder et al (2005) because our PVAR model measures the cross-sectional interaction among individuals in the panel and considers exogenous regressors. In Appendix 2, the estimation procedure for the extended PVAR-X model is presented.

4. Patent and firm-level data

We use data from several sources. The U.S. utility patent data set for the January 1979 - June 2005 period was purchased from MicroPatents and for the 1963-1978 period was obtained from the NBER patent data files. The U.S. patent database includes the USPTO patent number, application date, publication date, USPTO patent number of cited patents, 3-digit U.S. technological class and assignee name (company name if the patent was assigned to a firm) for each patent. Company specific information was downloaded from the Standard & Poor's Compustat data files. Then, we created a match file and crossed the patent data set with the firm database via the 6-digit Compustat CUSIP codes. Firm-specific data was corrected for inflation using consumer price index data from the U.S. Department of Labor, Bureau of Labor Statistics. Finally, we obtained annual data on the S&P500

[16]In the literature, several papers have analyzed likelihood-based estimation of dynamic panel data models. See for example, Balestra and Nerlove (1966), Nerlove (1971), Bhargava and Sargan (1983), Nerlove and Balestra (1996) for dynamic panel data models with random effects and Lancaster (2002), Hsiao et al (2002), Groen and Kleibergen (2003), Bun and Carree (2005), Kruiniger (2008), Dhaene and Jochmans (2010) for more recent dynamic panel data models that consider fixed effects as well.

stock market return over the 1979-2000 period from the Compustat data files. In the data procedures, we closely followed the recommendations of Hall et al (2001). In the remaining part of this chapter, we describe some details of the database procedures and construction of additional exogenous variables in the patent count data model.

4.1. Time of patents

The patent data set contains application date and issue (publication) date for each patent. As proposed by Hall et al (2001) we use the application date in order to determine the time of an innovation because inventors have incentive to apply for patent as soon as possible after completing the innovation.

4.2. Application-publication-lag

The U.S. patent database contains patents published until June 2005. This means that the data set excludes patents, which were submitted to the Patent Office before June 2005 but were not published before the end of our sample. It order to investigate the impact of the sample truncation, we analyze the distribution of the application-grant-lag (i.e., time elapsed between the publication date and the application date of a patent) in 1997, a year which is already not affected by the sample truncation bias. We find that 95.7 percent of patents are granted within 4.5 years after submission. (See Figure 1.) Therefore, we use a 4.5-year safety-lag and include data on patents with application dates until December 2000. (Hall et al, 2001 recommend an at least 3-year safety lag.)

[APPROXIMATE LOCATION OF FIGURE 1.]

4.3. Quality of knowledge, citation-lag

We compute a measure of patent quality based on the number of citations received by each patent granted between January 1963 and June 2005. We measure the *quality of knowledge* represented by a patent by computing the number of citations the patent receives from future patents (see also Hall et al, 2001). Nevertheless, the number of citations a patent receives from future patents is subject to sample truncation bias because the sample excludes future patents, which may potentially cite the observed patents. (See Figure 2.) In order to solve the truncation problem related to citation-lag, we employ the fixed-effects approach of Hall et al (2001) that is we divide the number of citations received figures by the average number of citations in the corresponding year and technological category. The technological categories are defined as in Hall et al (2001) that is (1) chemical, (2) computers and communications, (3) drugs and medical, (4) electrical and electronics, (5) mechanical and (6) others. (See Figures 3 and 4.)

[APPROXIMATE LOCATION OF FIGURES 2, 3, 4.]

4.4. Industry classification

In the data set used for the estimation of the patent count data model of Blazsek and Escribano (2010), we use the modified standard industry classification (SIC) of Hall and Mairesse (1996) that is (1) paper and printing, (2) chemicals, (3) rubber and plastics, (4) wood and misc., (5) primary metals, (6) fabricated metals, (7) machinery, (8) electrical machinery, (9) autos, (10) aircrafts and other trans., (11) textiles and leather, (12) pharmaceuticals, (13) food, (14) computers and inst., (15) oil and (16) non-manufacturing. In this paper, we restrict our attention to the following six industries: (1) aircrafts (19 firms), (2) pharmaceuticals (96 firms), (3) computers (97 firms), (4) software (53 firms), (5) defense industry (11 firms) and (6) oil industry (14 firms). The aircrafts and oil industries are defined by the modified SIC classification of Hall and Mairesse (1996). Other industries are defined using the SCI classification as follows: SIC 2834 pharmaceutical preparations (pharmaceuticals), SIC 357 computers, computing machines (computers), SIC 381 search, detection, navigation, guidance (defense) and SIC 7372 software industry. The SIC classification of firms was downloaded from the Compustat data files.

4.5. Observable knowledge spillovers

Observable knowledge flow occurs between two firms if a patent of a company cites a previous patent of another firm. Our data set contains all U.S. utility patent citations made by patents granted during the observation period. Using the patent citations information, for each patent, we compute the *quality of knowledge* received through (a) self-citations: the patent cites previous patents of the same firm, i.e. it builds on past knowledge produced in the same firm, (b) intra-industry spillovers: the patent cites previous patents of other firms in the same industry, i.e. knowledge spills over from the same sector and (c) inter-industry spillovers: the patent cites previous patents in different industries, i.e. knowledge spills over from other sectors.

Figure 5 shows that high-tech firms benefit more from intra-industry spillovers than non-hi-tech firms. Nevertheless, non-hi-tech firms benefit more from inter-industry spillovers. Not surprisingly, the total volume of knowledge flow is significantly higher for hi-tech firms than for non-high-tech firms. Figure 6 shows some interesting differences between industries. For example, intra-industry spillovers seem to be very important in the computer industry, while the aircrafts, car, rubber, metals, textil, food and non-manufacturing industries benefit more from knowledge produced in other industries. Self-citations seem to be more significant in the drugs, oil, paper, chemical and electrical machinery industries.

Clearly, the citation information is again subject to the citation-lag truncation bias because patents in the beginning of the observation period have less chance to cite previous and observed patents. After analyzing the citation-lag distribution (i.e. the distribution of time elapsed between citing and cited patent publication dates) we decided to use a 10-year safety-lag (from 1969) and only include patents in the sample from 1979.

[APPROXIMATE LOCATION OF FIGURES 5, 6.]

5. Empirical results

In this section, we present the estimation results obtained for six industries: aircrafts, pharmaceuticals, computers, software, defense and oil sectors. We cover all these industries in the next subsections where we overview the estimation results obtained for the univariate LFP and PVAR-X models.

The evolution of patent applications counts over 1979-2000 for each industry is presented in Figures 7 and 8. The evolution of mean industry observable and latent patent intensity components estimates is presented in Figures 9-14. R&D rankings of companies are presented in Table 1. The concentration of patent counts measured by the Herfindahl index is presented in Table 2 for each industry. The definition of R&D leadership according to alternative definitions is presented in Table 3. Parameters estimates of the PVAR-X model are presented in Table 4.

[APPROXIMATE LOCATION OF TABLES 1, 2 AND FIGURES 7, 8.]

In order to simplify to discussion, in the remaining part of this section we use y_{it} for stock returns, λ_{it}^{o} for the observable component of patent intensity, λ_{it}^{*} for the latent component of patent intensity of firm i in period t. Moreover, we use $\overline{y}_t$ for S&P500 stock market returns in year t, λ_{jt}^{o} for the R&D leaders' observable component of patent intensity, and λ_{jt}^{*} for the R&D leaders' latent component of patent intensity for firm j in period t.[17]

5.1. Aircrafts sector

Our sample includes $N = 19$ companies in the aircrafts sector. Figures 7 and 8 show that patent activity in this industry has been relatively stable during 1979-2000. During the 80s there was a peak in patent intensity but from 1990 it stabilized on a constant level. Moreover, Figure 9 evidences that although the observable component of patent intensity has increased steadily during 1979-2000, the latent component balanced it by a slow decreasing tendency. We can also see that the average level of the observable component has been 4-5 times higher than that of the latent component during the 90s. In Table 2, we can see that the concentration of patent counts among firms measured by the Herfindahl index is relatively low – with the value of 0.15 – compared to other industries. Nevertheless, from Tables 1 and 3a it can be observed that three companies dominate overall patent applications counts in the sector: Honeywell, Inc., United Technologies Co., and Allied-Signal Co. In Table 3a, we can see that until the end of the 80s, Honeywell, Inc. was the sector R&D leader. However, during the 90s United Technologies Co. and Allied-Signal Co. has become the leader according to alternative definitions of R&D leadership. According to definition 3(c) for some years Sundstrand Co. and Lockheed Martin Co. leaded R&D activity in the aircrafts industry. Table 4a presents the parameters estimates of the PVAR model for alternative definitions of R&D leadership. We find the next results for the ζ matrix:

- First, the PVAR(1) model is stationary for all definitions (see the eig figures in Table 4a).
- Second, we always find high positive autocorrelation for λ_{it}^{o} and λ_{it}^{*}. Moreover, we evidence positive but lower autocorrelation of y_{it}.

[17] Notice that for simplification reasons we do not use the 'ln' notation with the patent intensities.

- Third, the dynamic impact of both λ^o_{it-1} and λ^*_{it-1} is significantly positive on y_{it}. However, for most definitions of R&D leadership the impact of λ^o_{it-1} is higher.

- Fourth, we find evidence of causality between λ^o_{it} and λ^*_{it} in the following sense. We find that the dynamic impact of λ^o_{it-1} on λ^*_{it} is highly significant and positive, while the effect of λ^*_{it-1} on λ^o_{it} is not significant.

- Fifth, the dynamic impact of y_{it-1} on λ^o_{it} is positive in most cases while on λ^*_{it} it is significantly negative in most cases.

Regarding the variance-covariance matrix, Ω_ϵ that measures the contemporaneous interaction among endogenous variables we find the next results:

- First, there is non-significant but positive interaction between λ^o_{it} and λ^*_{it}.

- Second, there is significant negative interaction between y_{it} and λ^o_{it}.

- Third, we evidence a significant and positive interaction between y_{it} and λ^*_{it}.

Reviewing the estimates of the ζ_L matrix, which captures the influence of the R&D leaders' observable and latent patent activity our results evidence the followings:

- First, the impact of both λ^o_{jt-1} and λ^*_{jt-1} on y_{it} is significantly negative in most cases.

- Second, λ^o_{jt-1} has negative effect on both λ^o_{it} and λ^*_{it} for definitions 1(a)(b) and 3(a)(b)(c). However, we find positive effect on λ^o_{it} in definitions 1(c) and 2(a)(b)(c).

- Third, λ^*_{jt-1} has positive effect on both λ^o_{it} and λ^*_{it} in definitions 1 and 2. Nevertheless, for definition 3 we find negative impacts of λ^*_{jt-1} on λ^o_{it} and λ^*_{it}.

Finally, the impact of $\overline{y}_t$ measured by the β parameter vector shows the following results:

- First, we find significant and positive impact of $\overline{y}_t$ on y_{it}.

- Second, we find significant negative effect of $\overline{y}_t$ for both λ^o_{it} and λ^*_{it} in most cases.

[APPROXIMATE LOCATION OF TABLES 3a, 4a, FIGURE 9.]

5.2. Pharmaceuticals sector

Our sample includes $N = 96$ companies in the pharmaceuticals sector. Figures 7 and 8 show that patent activity in this industry has increased steadily during 1979-2000 with a local peak in 1995. Moreover, Figure 10 evidences that both the observable and latent components has increased during 1979-2000. We can also see from this figure that until the beginning of the 90s the level of observable and latent patent intensity components was similar. Nevertheless, from 1988/89 the observable component has increased at a higher rate every year. As a consequence, the level of the observable component was about 3 times higher than that of the latent component in the second half of the 90s. In Table 2, we can see that the concentration of patent counts among firms measured by the Herfindahl index is relatively low – with the value of 0.09 – compared to other industries. Nevertheless, from Tables 1 and 3b it can be observed that Merck & Co., Inc. dominate overall patent applications counts in the sector. In Table 3b, we can see that according to definitions 3(a)(b) Merck & Co., Inc. has always been the R&D leader. Nevertheless, when definition 3(c) is considered, we see that in some years Warner-Lambert Co. and Eli Lilly and Co. has been the leader in the drugs sector. Table 4b presents the parameters estimates of the PVAR model for alternative definitions of R&D leadership. We find the next results for the ζ matrix:

- First, the PVAR(1) model is stationary for all definitions (see the eig figures in Table 4b).
- Second, we always find high positive autocorrelation for λ_{it}^{o} and λ_{it}^{*}. However, we evidence lower and negative autocorrelation of y_{it}.
- Third, the dynamic impact of λ_{it-1}^{o} is significantly positive on y_{it}. However, the impact of λ_{it-1}^{*} on y_{it} is not significant.
- Fourth, we find evidence of causality between λ_{it}^{o} and λ_{it}^{*} in the following sense. We find that the dynamic impact of λ_{it-1}^{o} on λ_{it}^{*} is highly significant and positive, while the effect of λ_{it-1}^{*} on λ_{it}^{o} is not significant and negative.
- Fifth, the dynamic impact of y_{it-1} is positive both on λ_{it}^{o} and λ_{it}^{*}.

Regarding the variance-covariance matrix, Ω_{ϵ} that measures the contemporaneous interaction among endogenous variables we find the next results:

- First, there is no significant interaction between stock returns and the latent component of patent intensity.
- Second, there is significant positive interaction between y_{it} and λ_{it}^{o}.
- Third, there is positive but not always significant interaction between λ_{it}^{o} and λ_{it}^{*}.

Reviewing the estimates of the ζ_L matrix, which captures the influence of the R&D leaders' observable and latent patent activity our results evidence the followings:

- First, there is positive impact of λ_{jt-1}^{o} on y_{it} and λ_{it}^{o}, while it has negative influence on λ_{it}^{*}.
- Second, there is negative effect of λ_{jt-1}^{*} on y_{it} in definitions 1 and 3(a)(b). However, there is positive influence of λ_{jt-1}^{*} on y_{it} according to definitions 2 and 3(c).
- Third, λ_{jt-1}^{*} has positive impact on λ_{it}^{o} in definition 2. Nevertheless, λ_{jt-1}^{*} has negative influence on λ_{it}^{o} in definitions 1 and 3.
- Fourth, λ_{jt-1}^{*} has negative impact on λ_{it}^{*} in definitions 1, 3 and 2(a)(c). Nevertheless, λ_{jt-1}^{*} has positive effect on λ_{it}^{*} according to definition 2(b).

Finally, the impact of the S&P500 market return measured by the β parameter vector shows the following results:

- First, we find significant and positive impact of $\overline{y}_t$ on y_{it}.
- Second, $\overline{y}_t$ has significant positive effect on λ^o_{it}.
- Third, for λ^*_{it} we find less significant effects of $\overline{y}_t$.

[APPROXIMATE LOCATION OF TABLES 3b, 4b, FIGURE 10.]

5.3. Computers sector

Our sample includes $N = 97$ companies in the computers sector. Figures 7 and 8 show that patent activity in this industry has increased very significantly during 1979-2000. From the beginning of the 90s, this sector produced the most patents in our data set. Moreover, Figure 11 evidences that both the observable and latent patent intensity components have increased during 1979-2000. Nevertheless, during the entire sample period, the observable component has increased at a higher rate every year. As a consequence, the level of the observable component was about 4-5 times higher than that of the latent component in the second half of the 90s. In Table 2, we can see that the concentration of patent counts among firms measured by the Herfindahl index is relatively high – with the value of 0.23 – compared to other industries. From Tables 1 and 3c it can be observed that IBM Co. dominates overall patent applications counts in the sector during 1979-2000. Table 4c presents the parameters estimates of the PVAR model for alternative definitions of R&D leadership. We find the next results for the ζ matrix:

- First, the PVAR(1) model is stationary for all definitions (see the eig figures in Table 4b).
- Second, we always find high positive autocorrelation for λ^o_{it} and λ^*_{it}. However, we evidence lower and negative autocorrelation of y_{it}.
- Third, the dynamic impact of λ^o_{it-1} and λ^*_{it-1} is significantly positive on y_{it}. However, for most definitions the impact of λ^o_{it-1} is higher.
- Fourth, we find evidence of causality between λ^o_{it} and λ^*_{it} in the following sense. We find that the dynamic impact of λ^o_{it-1} on λ^*_{it} is highly significant and positive, while the effect of λ^*_{it-1} on λ^o_{it} is not significant (however negative).
- Fifth, the dynamic impact of y_{it-1} on λ^o_{it} and λ^*_{it} is not significant.

Regarding the variance-covariance matrix, Ω_ϵ that measures the contemporaneous interaction among endogenous variables we find the next results:

- First, there is significant positive interaction between λ^*_{it} and y_{it}.

- Second, there is no significant contemporaneous interaction among the rest of the variables.

Reviewing the estimates of the ζ_L matrix, which captures the influence of the R&D leaders' observable and latent patent activity our results evidence the followings:

- First, the impact of λ^o_{jt-1} both on y_{it} and λ^o_{it} is not significant in definitions 1, 2(a)(b) and 3. However, it is significantly positive according to definition 2(c).

- Second, λ^o_{jt-1} has significant negative effect on λ^*_{it}.

- Third, λ^*_{jt-1} has significant positive effect both on y_{it} and λ^o_{it}. Nevertheless, λ^*_{jt-1} has significant negative effect on λ^*_{it}.

Finally, the impact of the S&P500 market return measured by the β parameter vector shows the following results:

- First, we find significant and positive impact of $\overline{y}_t$ on y_{it}.

- Second, we find significant positive effect of $\overline{y}_t$ on λ^o_{it}.

- Third, there is negative impact of $\overline{y}_t$ on λ^*_{it} according to definitions 1 and 3, while there is no significant effect according to definition 2.

[APPROXIMATE LOCATION OF TABLES 3c, 4c, FIGURE 11.]

5.4. Software sector

Our sample includes $N = 53$ companies in the software sector. Figures 7 and 8 show that patent activity in this industry has increased very significantly during 1979-2000. Moreover, Figure 12 evidences that both the observable and latent components of patent intensity have increased steadily during 1979-2000. Nevertheless, we can also see that the average level of the observable component has been 8-10 times higher than that of the latent component in the end of the 90s. In Table 2, we can see that the concentration of patent counts among firms measured by the Herfindahl index is relatively high – with the value of 0.21 – compared to other industries. From Tables 1 and 3d it can be observed that Microsoft Co. dominates overall patent applications counts in the sector. Regarding the evolution of R&D leadership, we can see in Table 3d that until 1983/84 Atari, Inc. was the R&D leader in the software sector. Then, it was substituted by a competitor and until 1994/95 Wang Laboratories, Inc. dominated the sector's R&D activity. Finally, from the mid-90s Microsoft Co. has taken over R&D leadership in the industry. Table 4d presents the parameters estimates of the PVAR model for alternative definitions of R&D leadership. We find the next results for the ζ matrix:

- First, the PVAR(1) model is stationary for all definitions (see the eig figures in Table 4d).

- Second, we always find high positive autocorrelation for λ^o_{it} and λ^*_{it}. Moreover, we do not evidence significant autocorrelation of y_{it}.

- Third, there is no significant dynamic impact of λ^o_{it-1} and λ^*_{it-1} on y_{it}.
- Fourth, we find evidence of causality between λ^o_{it} and λ^*_{it} in the following sense. We find that the dynamic impact of λ^o_{it-1} on λ^*_{it} is highly significant and positive, while the effect of λ^*_{it-1} on λ^o_{it} is not significant.
- Fifth, there is significant dynamic impact of y_{it-1} on λ^o_{it} and λ^*_{it}.

Regarding the variance-covariance matrix, Ω_ϵ that measures the contemporaneous interaction among endogenous variables we find the next results:

- First, there is significant positive interaction between y_{it} and λ^o_{it}.
- Second, λ^*_{it} has no significant interaction with y_{it} and λ^o_{it}.

Reviewing the estimates of the ζ_L matrix, which captures the influence of the R&D leaders' observable and latent patent activity our results evidence the followings:

- First, the impact of λ^o_{jt-1} and λ^*_{jt-1} on y_{it} is positive in leader definitions 1, 2, 3(a)(b). The impact of the leaders' latent component is especially high in definitions 1 and 2. However, λ^*_{jt-1} has negative impact on y_{it} in definition 3(c).
- Second, the effect of λ^o_{jt-1} and λ^*_{jt-1} on λ^o_{it} is positive.
- Third, the influence of λ^o_{jt-1} and λ^*_{jt-1} on λ^*_{it} is negative.

Finally, the impact of the S&P500 market return measured by the β parameter vector shows the following results:

- First, we find significant and positive impact of $\overline{y}_t$ on y_{it}.
- Second, we find significant positive effect of $\overline{y}_t$ on λ^o_{it}.
- Third, we find significant negative effect of $\overline{y}_t$ on λ^*_{it} in definitions 1, 2, 3(a)(b). Nevertheless, we find significant positive effect of $\overline{y}_t$ on λ^*_{it} in definition 3(c).

[APPROXIMATE LOCATION OF TABLES 3d, 4d, FIGURE 12.]

5.5. Defense sector

Our sample includes $N = 11$ companies in the defense sector. Figures 7 and 8 show that patent activity in this industry has increased 1979-2000. The increasing tendency was more significant during the 90s. until 1997. Moreover, Figure 13 evidences that the increasing trend of patent applications has been driven by the observable component as the latent component of patent intensity has been relatively stable during 1979-2000. We can also observe in Figure 13 that until 1994/95 the latent component was superior to the observable one. Until the beginning of the 90s the level of the log latent component was about twice of the log observable component. However, in the end of the 90s we can see just the opposite relation between the observable and latent components of patent intensity. This is due to the fact that during the 90s the observable part has increased very significantly while the latent component stayed approximately at the same level. In Table 2, we can see that the concentration of patent counts among firms measured by the Herfindahl index is high – with the value of 0.31 – compared to other industries. From Tables 1 and 3e it can be observed that three companies dominate overall patent applications counts in the sector: Raytheon Co., Northrop Co., and Litton Systems, Inc. Moreover, we can see in Table 3e that according the definitions 3(a)(b), Raytheon Co. has always been the R&D leader during 1979-2000. However, when definition 3(c) is used we can see that from 1994 Litton Systems, Inc and Northrop Co. have taken over R&D leadership. Table 4e presents the parameters estimates of the PVAR model for alternative definitions of R&D leadership. We find the next results for the ζ matrix:

- First, the PVAR(1) model is stationary for all definitions (see the eig figures in Table 4f).
- Second, we always find high positive autocorrelation for λ^o_{it} and λ^*_{it}. Moreover, we evidence significant negative autocorrelation of y_{it}.
- Third, the dynamic impact of λ^o_{it-1} is significantly positive on y_{it}. However, the impact of λ^*_{it-1} on y_{it} is not significant.
- Fourth, we find evidence of causality between λ^o_{it} and λ^*_{it} in the following sense. We find that the dynamic impact of λ^o_{it-1} on λ^*_{it} is highly significant and positive, while the effect of λ^*_{it-1} on λ^o_{it} is not significant.
- Fifth, the dynamic impact of y_{it-1} on λ^o_{it} and λ^*_{it} is positive.

Regarding the variance-covariance matrix, Ω_ϵ that measures the contemporaneous interaction among endogenous variables we find significant positive interaction between all variables.

Reviewing the estimates of the ζ_L matrix, which captures the influence of the R&D leaders' observable and latent patent activity our results evidence the followings:

- First, the impact of λ^o_{jt-1} on y_{it} and λ^*_{it} is negative. Nevertheless, the same impact is significantly positive on λ^o_{it}.
- Second, λ^*_{jt-1} has positive influence on y_{it} in all definitions.
- Third, λ^*_{jt-1} has negative effect on λ^o_{it} in definitions 1 and 3. On the other hand, λ^*_{jt-1} has significant and positive impact on λ^o_{it} in definition 2.
- Fourth, λ^*_{jt-1} has positive influence on λ^*_{it} in definitions 1 and 3. However, it has significant negative influence on λ^*_{it} when definition 2 is considered.

Finally, the impact of the S&P500 market return measured by the β parameter vector shows the following results:

- First, we find significant and positive impact of $\overline{y}_t$ on y_{it}.
- Second, we find significant positive effect of $\overline{y}_t$ on λ_{it}^o.
- Third, $\overline{y}_t$ has positive impact on λ_{it}^* in definitions 1 and 3(a)(b). Nevertheless, the same impact is non-significant for definition 2 and significantly negative for definition 3(c).

[APPROXIMATE LOCATION OF TABLES 3e, 4e, FIGURE 13.]

5.6. Oil sector

Our sample includes $N = 14$ companies in the oil sector. Figures 7 and 8 show that patent activity in this industry has decreased permanently during 1979-2000. Moreover, Figure 14 evidences that this decreasing trend has been driven by the latent component as that has decreased steadily during 1979-1997. The fall in the latent component has been compensated partly by the slightly increasing observable component. However, the overall tendency of patent applications counts has been negative during the sample period. We can also see in Figure 14 that until 1984 the level of the observable and latent components was approximately identical. However, from 1985 the difference between the observable and the latent components of patent activity has opened and in the second half of the 90s the log observable part has been around 5-6 times higher than the log latent component. In Table 2, we can see that the concentration of patent counts among firms measured by the Herfindahl index is relatively low – with the value of 0.15 – compared to other industries. From Tables 1 and 3f it can be observed that seven firms dominate overall patent applications counts in the sector: Exxon Co., Mobil Oil Co., Shell Oil Co., Phillips Petroleum Co., Texaco, Inc., Chevron Research Co., and Atlantic Richfield Co. In Table 3f, we can see that until 1984 Exxon Co., Phillips Petroleum Co. or Mobil Oil Co. dominated R&D leadership depending on which definition is considered. Then, until 1996/98 Mobil Oil Co. was to R&D leader. Nevertheless, during the last years of the sample, Exxon Co. has become the R&D leader in the oil sector. Table 4f presents the parameters estimates of the PVAR model for alternative definitions of R&D leadership. We find the next results for the ζ matrix:

- First, the PVAR(1) model is stationary for all definitions (see the eig figures in Table 4f). However, we note that the maximum eigenvalue is very close to the unit circle in the oil sector for all R&D leadership definitions.
- Second, we always find high positive autocorrelation for λ_{it}^o and λ_{it}^*. Moreover, we do not evidence significant autocorrelation of y_{it}.
- Third, the dynamic impact of the λ_{it-1}^* on y_{it} is positive. Nevertheless, the dynamic impact of λ_{it}^o on y_{it} is not significant.
- Fourth, we find weak positive lagged interaction between λ_{it}^o and λ_{it}^*.
- Fifth, the dynamic impact of y_{it-1} on λ_{it}^o and λ_{it}^* is non-significant.

Regarding the variance-covariance matrix, Ω_ϵ that measures the contemporaneous interaction among endogenous variables we find the next results:

- First, there is weak negative contemporaneous interaction between y_{it} and λ_{it}^o.
- Second, there is significant positive interaction between λ_{it}^o and λ_{it}^*.
- Third, there is weak positive or non significant interaction – depending on the leader definition – between y_{it} and λ_{it}^*.

Reviewing the estimates of the ζ_L matrix, which captures the influence of the R&D leaders' observable and latent patent activity our results evidence the followings:

- First, λ_{jt-1}^o has positive influence on y_{it} and λ_{it}^o.
- Second, λ_{jt-1}^o has positive impact on λ_{it}^* in definitions 1, 2 and 3(a). However, it has negative impact on λ_{it}^* in definition 3(b) and non-significant effect for definition 3(c).
- Third, λ_{jt-1}^* has negative effect on λ_{it}^o.
- Fourth, λ_{jt-1}^* has negative effect on y_{it} in definitions 1 and 2. Nevertheless, for definition 3 we evidence the positive sign for this effect.
- Fifth, λ_{jt-1}^* has significant positive influence on λ_{it}^*.

Finally, the impact of the S&P500 market return measured by the β parameter vector shows the following results:

- First, we find positive impact of $\overline{y}_t$ on y_{it} in definitions 1, 2 and 3(b). However, for definitions 1(c) and 3(a) we evidence the opposite relationship.
- Second, $\overline{y}_t$ has significant positive effect both on λ_{it}^o and λ_{it}^*.

[APPROXIMATE LOCATION OF TABLES 3f, 4f, FIGURE 14.]

6. Conclusions

In this paper, we employ dynamic panel data models that identify the interaction among stock returns, observable and latent patent activity for a large U.S. data set over a 22-year time period: 1979-2000. We focus on the following six industries: aircrafts, pharmaceuticals, computers, software, defense and oil sectors and include a large number of firms in our investigation.

We estimate two models consecutively: First, a univariate LFP dynamic patent count data model, suggested by Blazsek and Escribano (2010), to separate the observable and latent components of patent intensity for each company. Second, a multivariate PVAR-X model to identify the inter-firm interaction among competitors and to study the impact of R&D leader firms on competitors. In the count data model applied in the first step, dynamic latent variables are included, which complicates the statistical inference of the econometric model. The MSL estimation of this model is performed using the EIS technique of Richard and Zhang (2007). In the PVAR-X model employed in the second step, we consider an extension of the QML methodology suggested by Binder et al (2005) because we consider exogenous variables and cross-sectional interaction among individuals in the panel.

We find that in all industries the observable intensity component has increased during 1979-2000. The latent component has increased in the pharmaceuticals, computers, software and defense sectors. It has decreased in the aircrafts and oil industries. Investigating the influence of R&D leader firms' patent intensity components on competitors stock returns and patent intensity we find that both observable and latent patent intensity components had significant impact on competitors' market value and patent activity. Finally, the PVAR estimates suggest different effects of R&D leaders on R&D followers in each industry.

Acknowledgments

The concept of this paper started when the first author visited GREQAM, Marseille in 2003. He also acknowledges the research scholarship of CREST, Paris and the MICFINMA research network financed by the European Union and research financing of the PIUNA project at Universidad de Navarra. In this context, he would like to thank Luc Bauwens for useful discussions and Luis Albériko Gil-Alana, Christian Gouriéroux, Bronwyn Hall, Jerry Hausman, Javier Hualde, Thierry Kamionka, Germán López Espinosa, Michel Lubrano, Velayoudom Marimoutou, Antonio Moreno, János Pákozdy, Mikel Tapia and other members of CREST, GREQAM, Universidad Carlos III de Madrid and Universidad de Navarra for all support. Special thanks go to Luc Bauwens and Nikolaus Hautsch for providing the original GAUSS code for the estimation of their latent-factor intensity models. The authors thank to participants of the ETSERN Pamplona Meeting, June 2010, for helpful discussions and comments.

Data sources

MicroPatents Co., U.S. Utility Patent Database covering the 1979-2004 period and U.S. patent citations for years 2003 and 2004.

National Bureau of Economic Research Patent Citations Data-File. CD-ROM included in: Jaffe, A. B., M. Trajtenberg (Eds.), Patents, Citations, and Innovations: A Window on the Knowledge Economy, MIT Press, 2002.

Compustat (North America) Database. Standard & Poor's, 2005.

Consumer price index for all urban consumers. U.S. Department of Labor: Bureau of Labor Statistics, data downloaded from the Federal Reserve Bank of St. Louis website (http://research.stlouisfed.org).

Appendix 1: Patent intensity estimation by EIS

The LFP dynamic patent count data model is estimated by MSL method (Gouriéroux and Monfort, 1991) using the EIS technique of Richard and Zhang (2007). The EIS method has been successfully applied for the evaluation of likelihood functions involving high-dimensional integrals for example in stochastic volatility models (Liesenfeld and Richard, 2003) and stochastic conditional intensity models (Bauwens and Hautsch, 2006).

Denote $\mathcal{L}$ the likelihood of observed patent counts:

$$\mathcal{L}(N_T, \theta) = \int_{\mathbb{R}^T} \prod_{i=1}^{N} g(N_{iT}, L_T^*|Q_T, \theta) dL_T^* = \int_{\mathbb{R}^T} \prod_{t=1}^{T} \prod_{i=1}^{N} g_t(n_{it}, l_t^*|N_{it-1}, L_{t-1}^*, Q_t, \theta_t) dL_T^*, \tag{A1.1}$$

where g is the joint density of patent counts and latent variables for firm i and θ denotes the vector of parameters of the model. Notice that we integrate out all latent variables from g in the first equality to obtain the marginal density of patent counts and that we factorize g to a product of conditional densities in the last equality.

The major difficulty related to the statistical inference of the model is the precise evaluation of the T-dimensional integral in $\mathcal{L}$ for given parameter values. This is performed numerically by Monte Carlo (MC) simulation method using the EIS technique (Richard and Zhang, 2007). We note that the EIS procedure is nested into a typical likelihood function maximization procedure. In order to maintain the stability of that procedure for every set of parameters, we use the same set of i.i.d $N(0, 1)$ so-called *common random numbers* (see Richard and Zhang, 2007) to estimate the value of the likelihood function.

The EIS methodology consists of the following elements. First, we introduce an *auxiliary sampler*, m, which is included into the likelihood function and then factorized into the product of T sequential auxiliary densities, $\{m_t : t = 1, \ldots, T\}$ as follows:

$$\mathcal{L}(N_{iT}, \theta) = \int_{\mathbb{R}^T} \prod_{t=1}^{T} \frac{g_t(n_{it}, l_t^*|N_{it-1}, L_{t-1}^*, Q_t, \theta_t)}{m_t(l_t^*|L_{t-1}^*, \theta_t^*)} \times m_t(l_t^*|L_{t-1}^*, \theta_t^*) dL_T^*, \tag{A1.2}$$

where θ_t^* denotes the parameters of the i-th auxiliary sampler. Then, the *importance MC estimate* of $\mathcal{L}(N_{iT}, \theta)$ for given θ^* is:

$$\hat{L}_R(N_{iT}, \theta, \theta^*) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \frac{g_t(n_{it}, l_{tr}^*|N_{it-1}, L_{t-1r}^*, Q_t, \theta_t)}{m_t(l_{tr}^*|L_{t-1r}^*, \theta_t^*)}, \tag{A1.3}$$

where θ^* is the vector of parameters of the auxiliary sampler defined as the *union* of all θ_t^*s and $\{l_{tr}^* : t = 1, \ldots, T\}$ denotes the r-th trajectory of i.i.d draws from $\{m_t : t = 1, \ldots, T\}$ and $r = 1, \ldots, R$. There are two questions arising related to the above formulation: (a) How to choose m_t? and (b) How to choose the θ_t^* parameters?

(a) Richard and Zhang (2007) suggest to define the auxiliary sampler, m_t with its associated density kernel, k_t:

$$k_t(L_t^*, \theta_t^*) = m_t(l_t^*|L_{t-1}^*, \theta_t^*)\chi_t(L_{t-1}^*, \theta_t^*), \tag{A1.4}$$

where

$$\chi_t(L^*_{t-1}, \theta^*_t) = \int_{\mathbb{R}} k_t(L^*_t, \theta^*_t) dl^*_t \tag{A1.5}$$

denotes the t-th integrating constant associated to k_t. Richard and Zhang (2007) suggest to choose k_t as a normal density kernel. Following Bauwens and Hautsch (2006), we include f^*_t into the auxiliary sampler m_t. Therefore, the t-th normal density kernel has the following form:

$$k_t(L^*_t, \theta^*_t) = \exp(\theta^*_{t1} l^*_t + \theta^*_{t2}(l^*_t)^2) \times \exp\left(-\frac{(l^*_t - \mu l^*_{t-1})^2}{2}\right), \tag{A1.6}$$

where $\theta^*_t = (\theta^*_{t1}, \theta^*_{t2})$ determines the conditional mean and variance of the t-th auxiliary sampler m_t. We can find that the conditional mean, μ_t and conditional variance, π^2_t of the normal auxiliary sampler, m_t are given by the following expressions (Bauwens and Hautsch, 2006):

$$\mu_t = \pi^2_t(\theta^*_{t1} + \mu l^*_{t-1}) \tag{A1.7}$$

$$\pi^2_t = \frac{1}{1 - 2\theta^*_{t2}} \tag{A1.8}$$

Therefore, for given parameters of the auxiliary sampler a trajectory of $\{l^*_t : t = 1, \ldots, T\}$ can be generated from the following AR(1) process:

$$l^*_t = \pi^2_t \theta^*_{t1} + \pi^2_t \mu l^*_{t-1} + \pi_t \eta_t, \tag{A1.9}$$

where $\eta_t \sim N(0, 1)$ are i.i.d common random numbers. Moreover, from (A1.6) we may deduce that the t-th integrating constant is given by:

$$\chi_t(L^*_{t-1}, \theta^*_t) = \sqrt{2\pi\pi^2_t} \times \exp\left(-\frac{\mu^2(l^*_{t-1})^2}{2} + \frac{\mu^2_t}{2\pi^2_t}\right). \tag{A1.10}$$

(b) The EIS methodology relies on the optimal choice of parameters of the auxiliary samplers in the sense that for given m the variance of $\hat{L}_R(N_{iT}, \theta, \theta^*)$ is minimized, i.e.:

$$\theta^*(N_{iT}, \theta) = \arg\min_{\theta^*} Var[\hat{L}_R(N_{iT}, \theta, \theta^*)]. \tag{A1.11}$$

From equation (A1.3) one can see that this variance is 'small' if the auxiliary sampler m_{it} provides a 'good fit' to the g_t function. Expressing the auxiliary sampler by its associated density kernel and integrating constant from (A1.4), we may say that m_t provides 'good fit' to g_t if

$$\ln g_t(n_{it}, l^*_t | N_{it-1}, L^*_{t-1}, Q_t, \theta_t) + \ln \chi_t(L^*_{t-1}, \theta^*_t) \simeq \ln k_t(L^*_t, \theta^*_t). \tag{A1.12}$$

Richard and Zhang (2007) show that if the auxiliary samplers are normal distributions then the MC variance minimization problem stated in equation (A1.11) can be reduced to a recursive sequence of T ordinary least squares (OLS) problems, each of the following form (see also Bauwens and Hautsch, 2006):

$$\ln g_t(n_{it}, l^*_{tr} | N_{it-1}, L^*_{t-1r}, Q_t, \theta) + \ln \chi_{t+1}(L^*_{tr}, \hat{\theta}^*_{t+1}) = \theta^*_{t0} + \theta^*_{t1} l^*_{tr} + \theta^*_{t2}(l^*_{tr})^2 + u_{tr} \tag{A1.13}$$

for $t = T, \dots, 1$, $r = 1, \dots, R$, $\chi_{T+1}(L^*_{iT}, \hat{\theta}^*_{T+1}) = 1$ and $\hat{\theta}^*_{t+1}$ is the OLS estimate of θ^*_{t+1}. Thus, for each observation t, one has to compute the OLS estimate of the parameters of the auxiliary sampler, m_t. The regressions have a recursive structure because we use the $\hat{\theta}^*_{t+1}$ estimates in order to compute the integrating constant for the next, t-th OLS regression. (This is based on the permutation of the integrating constants in equation (A1.3), see Richard and Zhang (2007) for more details.) Thus, the regressions are run backwards, i.e. from T to 1. The sample size of each regression is equal to the number of trajectories drawn, R. One of the advantages of the EIS algorithm is that these auxiliary regressions are typically run with relatively low sample sizes. In our case, the number of trajectories of the latent variables is $R = 50$. In summary, the EIS technique consists of the following steps:

- Step 1: Draw R trajectories $\{l^*_{tr}\}_{t=1}^{T}$ from the natural sampler, $N(\mu l^*_{t-1r}, 1)$.
- Step 2: for each t (from T to 1), estimate the regression in (A1.13).
- Step 3: Given the OLS estimates of θ^* obtained in Step 2, draw R trajectories $\{l^*_{tr}\}_{t=1}^{T}$ from the auxiliary samplers, $\{m_t\}_{t=1}^{T}$. Iterate Steps 2 and 3 five times.
- Step 4: Compute the importance MC estimate of $\hat{L}_R$ according to (A1.3).

Appendix 2: PVAR-X with random effects estimation by QML method

In this appendix, we present the statistical inference applied for the PVAR-X model with *random effects*. We employ the methodology suggested by Binder et al (2005). First, recall the PVAR-X model to be estimated:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon) \tag{A2.1}$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \sum_{k=1}^{p} \zeta_{Lk} X_{jt-k} D_{Ljt}. \tag{A2.2}$$

Definitions of parameters in these equations have been presented in Section 2.1. We impose the next assumption about *random effects* to reduce the number of parameters in the numerical maximization procedure of the log-likelihood function:

Assumption 2 (Random effects). The random effect a_i is uncorrelated with the error term ϵ_{it} and uncorrelated with the initial condition of the observable variables $\tilde{X}_{i0}$, i.e. $Cov(a_i, \epsilon_{it}) = 0$ and $\Omega_{0a} = Cov(\tilde{X}_{i0}, a_i) = 0$ are 3×3 matrices of zeros.

In order to ensure the positive semi-definiteness and symmetry of the variance-covariance matrices of error terms Ω_ϵ, initial conditions Ω_0 and random effects Ω_a, we characterize these matrices by their corresponding lower triangular Cholesky matrices: $\sqrt{\Omega_\epsilon}$, $\sqrt{\Omega_0}$ and $\sqrt{\Omega_a}$, respectively. In addition, to identify the parameters in these matrices we impose the next assumption:

Assumption 3 (Diagonals of covariance matrices). The diagonals of the Ω_ϵ, Ω_0 and Ω_a matrices are restricted to ones:

$$\sqrt{\Omega_\epsilon} = \begin{pmatrix} 1 & 0 & 0 \\ \Omega_{\epsilon_{21}} & 1 & 0 \\ \Omega_{\epsilon_{31}} & \Omega_{\epsilon_{32}} & 1 \end{pmatrix} \quad \sqrt{\Omega_0} = \begin{pmatrix} 1 & 0 & 0 \\ \Omega_{0_{21}} & 1 & 0 \\ \Omega_{0_{31}} & \Omega_{0_{32}} & 1 \end{pmatrix} \quad \sqrt{\Omega_a} = \begin{pmatrix} 1 & 0 & 0 \\ \Omega_{a_{21}} & 1 & 0 \\ \Omega_{a_{31}} & \Omega_{a_{32}} & 1 \end{pmatrix} \tag{A2.3}$$

where the parameters of the Cholesky matrices are real numbers. To interpret the contemporaneous interaction among the endogenous variables, we compute the variance-covariance matrix as $\Omega_\epsilon = \sqrt{\Omega_\epsilon}\sqrt{\Omega_\epsilon}'$.[18]

Then, the *random effects* maximum likelihood estimator of the parameters

$$\theta = (\zeta, \Omega_\epsilon, \Omega_0, \Omega_a, \beta, \zeta_{L1}, \ldots, \zeta_{Lp})' \tag{A2.4}$$

[18] We employ the same strategy for the parameterization of the covariance matrices of random effects Ω_a and initial conditions Ω_0 in order to get the desired properties of these matrices. In the numerical maximization procedure of the likelihood function, we do not impose any restriction on the parameter values. The identification strategy used in this paper is similar to Blanchard and Quah (1989) and Gil-Alana and Moreno (2009).

is obtained by maximizing the following log-likelihood function:

$$\ln \mathcal{L}(\theta) = -\frac{3NT}{2}\ln(2\pi) - \frac{N}{2}\ln|\Sigma_\eta| - \frac{N}{2}\mathrm{tr}(\Sigma_X^{-1}S_X), \tag{A2.5}$$

where

$$\Sigma_\eta = \begin{pmatrix} \Omega_0 & \iota_T' \otimes \Omega_{0a}' \\ \iota_T \otimes \Omega_{0a} & I_T \otimes \Omega_\epsilon + \iota_T\iota_T' \otimes \Omega_a \end{pmatrix} \tag{A2.6}$$

with ι_T being a $T \times 1$ vector of ones, I_T being a $T \times T$ identity matrix and

$$S_X = \tfrac{1}{N}\textstyle\sum_{i=1}^N \tilde{\mathcal{X}}_i\tilde{\mathcal{X}}_i', \tag{A2.7}$$

where $\tilde{\mathcal{X}}_i = (\tilde{X}_{i1}, \ldots, \tilde{X}_{iT})'$. Finally, the Σ_X^{-1} matrix is defined as

$$\Sigma_X^{-1} = R^{-1}\Sigma_\eta R'^{-1} \quad \text{with} \quad R = \begin{pmatrix} I_3 & 0_3 & \ldots & \ldots & 0_3 \\ -\zeta & I_3 & \ddots & \ddots & \vdots \\ 0_3 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0_3 \\ 0_3 & \ldots & 0_3 & -\zeta & I_3 \end{pmatrix}, \tag{A2.8}$$

where 0_3 is a 3×3 matrix of zeros and I_3 being a 3×3 identity matrix.

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Table 1a. R&D ranking of firms for definitions 1 and 2 of R&D leadership

A. Aircrafts

Company name	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it}n_{it}$
Honeywell, Inc.	**4,545**	**3,732**	*207*
United Technologies Co.	*3,928*	*3,366*	*192*
Allied-Signal Co.	*2,958*	*2,589*	**216**
Sundstrand Data Control, Inc.	1,437	1,110	111
The B. F. Goodrich Co.	1,184	884	61
Lockheed Martin Co.	1,144	803	165
Brunswick Co.	891	727	50
Textron, Inc.	664	490	33
General Dynamics Co.	606	442	34
GenCorp, Inc.	238	216	19

B. Pharmaceuticals

Company name	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it}n_{it}$
Merck & Co., Inc.	**4,787**	**3,007**	**220**
Eli Lilly and Co.	*2,552*	*1,289*	*161*
Pfizer Inc.	*2,266*	*1,081*	*105*
Abbott Laboratories	*2,146*	*1,626*	*121*
Warner-Lambert Co.	1,797	*1,349*	94
Bristol-Myers Co.	1,533	752	85
American Home Products Co.	1,162	675	55
Johnson & Johnson	1,156	*1,088*	73
Genentech, Inc.	822	610	57
Alza Co.	781	900	36

C. Computers

Company name	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it}n_{it}$
IBM Co.	**32,939**	**36,701**	**2,099**
Xerox Co.	*9,981*	*11,094*	*519*
Hewlett-Packard Co.	*9,596*	*9,299*	*650*
Sun Microsystems, Inc.	3,549	3,664	*442*
Compaq Computer Co.	2,057	2,679	251
Seagate Technology	2,014	1,700	220
Pitney-Bowes, Inc.	1,799	1,550	82
Apple Computer, Inc.	1,461	1,736	160
3Com Co.	1,101	1,151	218
Dell USA Co.	793	1,174	102

Notes: Firms in each industry are ranked according to three alternative measures of R&D leadership:

(a) $\sum_{t=1}^{T} n_{it}$, where n_{it} denotes patent counts,

(b) $\sum_{t=1}^{T} \tilde{c}_{it}$, where $\tilde{c}_{it}$ denotes number of citations received from future patents corrected for sample truncation bias,

(c) $\sum_{t=1}^{T} \omega_{it}n_{it}$, where $\omega_{it} = \tilde{c}_{it}/\sum_{k=1}^{T} \tilde{c}_{ik}$ denotes the weighting term of patent counts.

Companies are classified to three groups according to this ranking. The firm in the first group is denoted by bold figures. The firms in the second group are denoted by italic and underlined figures. Remaining firms in each industry are assigned to the third group. According to definition 1 of R&D leadership, the company in group 1 is the sector's R&D leader. Definition 2 assigns R&D leadership to all firms in groups 1 and 2.

Table 1b. R&D ranking of firms for definitions 1 and 2 of R&D leadership

D. Software

Company name	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it} n_{it}$
Microsoft Co.	**3,319**	**3,590**	**419**
Oracle Co.	*<u>426</u>*	*<u>520</u>*	*<u>89</u>*
Adobe International, Inc.	247	155	31
Wang Laboratories, Inc.	240	389	17
Novell, Inc.	232	385	42
National Instrument Co, Inc.	219	191	23
Synopsys, Inc.	165	195	28
Cadence Design Systems, Inc.	134	106	18
Genesys Telc. Labs., Inc.	131	154	35
Autodesk, Inc.	122	53	22

E. Defense

Company name	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it} n_{it}$
Raytheon Co.	**1,922**	**1,285**	**111**
Northrop Co.	*<u>1,259</u>*	*<u>758</u>*	*<u>101</u>*
Litton Systems, Inc.	*<u>1,148</u>*	*<u>754</u>*	*<u>54</u>*
Garmin Co.	55	37	7
Edo Co.	53	34	4
Cubic Co.	41	28	3
SiRF Technology, Inc.	31	28	4
Orbital Sciences Co. II	25	31	2
KVH Industries, Inc.	17	13	5
Lowrance Electronics, Inc.	16	8	2

F. Oil

Company name	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it} n_{it}$
Exxon Co.	**5,516**	**4,977**	*<u>251</u>*
Mobil Oil Co.	*<u>5,002</u>*	*<u>4,812</u>*	**281**
Shell Oil Co.	*<u>4,444</u>*	*<u>3,446</u>*	*<u>213</u>*
Phillips Petroleum Co.	*<u>3,581</u>*	*<u>2,303</u>*	*<u>198</u>*
Texaco, Inc.	*<u>2,718</u>*	*<u>1,690</u>*	*<u>156</u>*
Chevron Research Co.	*<u>1,926</u>*	*<u>1,468</u>*	*<u>99</u>*
Atlantic Richfield Co.	*<u>1,499</u>*	*<u>1,185</u>*	*<u>83</u>*
Conoco, Inc.	794	571	50
Marathon Oil Co.	309	241	16
Great Lakes Carbon Co.	55	38	9

Notes: Firms in each industry are ranked according to three alternative measures of R&D leadership:

(a) $\sum_{t=1}^{T} n_{it}$, where n_{it} denotes patent counts,

(b) $\sum_{t=1}^{T} \tilde{c}_{it}$, where $\tilde{c}_{it}$ denotes number of citations received from future patents corrected for sample truncation bias,

(c) $\sum_{t=1}^{T} \omega_{it} n_{it}$, where $\omega_{it} = \tilde{c}_{it} / \sum_{k=1}^{T} \tilde{c}_{ik}$ denotes the weighting term of patent counts.

Companies are classified to three groups according to this ranking. The firm in the first group is denoted by bold figures. The firms in the second group are denoted by italic and underlined figures. Remaining firms in each industry are assigned to the third group. According to definition 1 of R&D leadership, the company in group 1 is the sector's R&D leader. Definition 2 assigns R&D leadership to all firms in groups 1 and 2.

Table 2. Concentration of the number of patent applications over 1979-2000

Industry	HI
A. Aircrafts	0.15
B. Pharmaceuticals	0.09
C. Computers	**0.23**
D. Software	**0.21**
E. Defense	**0.31**
F. Oil	0.15

Notes: The HI denotes Herfindahl-index. Industries with higher concentration of patent applications are written by bold letters.

Table 3a. R&D leader firms according to definitions 1, 2 and 3 of R&D leadership over 1979-2000

A. Aircrafts

year	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it}n_{it}$
Definition 1			
1979-2000	Honeywell, Inc.	Honeywell, Inc.	Allied-Signal Co.
Definition 2			
1979-2000	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1979-2000	United Technologies Co.	United Technologies Co.	United Technologies Co.
1979-2000	Allied-Signal Co.	Allied-Signal Co.	Allied-Signal Co.
Definition 3			
1979	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1980	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1981	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1982	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1983	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1984	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1985	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1986	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1987	Honeywell, Inc.	Honeywell, Inc.	Honeywell, Inc.
1988	Honeywell, Inc.	Honeywell, Inc.	United Technologies Co.
1989	Honeywell, Inc.	Honeywell, Inc.	United Technologies Co.
1990	Honeywell, Inc.	United Technologies Co.	Sundstrand Co.
1991	Honeywell, Inc.	United Technologies Co.	Allied-Signal Co.
1992	United Technologies Co.	United Technologies Co.	Allied-Signal Co.
1993	United Technologies Co.	United Technologies Co.	Allied-Signal Co.
1994	United Technologies Co.	United Technologies Co.	Allied-Signal Co.
1995	United Technologies Co.	United Technologies Co.	Allied-Signal Co.
1996	United Technologies Co.	United Technologies Co.	Allied-Signal Co.
1997	United Technologies Co.	Allied-Signal Co.	Allied-Signal Co.
1998	United Technologies Co.	Allied-Signal Co.	Allied-Signal Co.
1999	Honeywell, Inc.	Allied-Signal Co.	Lockheed Martin Co.
2000	Honeywell, Inc.	Allied-Signal Co.	Lockheed Martin Co.

Notes: We measure R&D leadership using three alternative variables: (a) The number of patent applications, n_{it}, (b) The number of patent citations received from future patents, $\tilde{c}_{it}$, and (c) The number of patent applications weighted by the number of citations received, $\omega_{it}n_{it}$, where $\omega_{it} = \tilde{c}_{it}/\sum_{k=1}^{T}\tilde{c}_{ik}$. R&D leaders according to definitions 1 and 2 are derived from Table 1 and by definition 3 are determined using the following formulas with $\delta = 15\%$:

Definition 3(a): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is}(1-\delta)^{(t-1)-s} : i = 1,\ldots,N \right\}$$

Definition 3(b): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is}(1-\delta)^{(t-1)-s} : i = 1,\ldots,N \right\}$$

Definition 3(c): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is}n_{is}(1-\delta)^{(t-1)-s} : i = 1,\ldots,N \right\}$$

Table 3b. R&D leader firms according to definitions 1, 2 and 3 of R&D leadership over 1979-2000

B. Pharmaceuticals

year	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it}n_{it}$
Definition 1			
1979-2000	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
Definition 2			
1979-2000	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1979-2000	Eli Lilly and Co.	Eli Lilly and Co.	Eli Lilly and Co.
1979-2000	Pfizer, Inc.	Pfizer, Inc.	Pfizer, Inc.
1979-2000	Abbott Laboratories	Abbott Laboratories	Abbott Laboratories
1979-2000		Warner-Lambert Co.	
1979-2000		Johnson & Johnson	
Definition 3			
1979	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1980	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1981	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1982	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1983	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1984	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1985	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1986	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1987	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1988	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1989	Merck & Co., Inc.	Merck & Co., Inc.	Warner-Lambert Co.
1990	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1991	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1992	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1993	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1994	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1995	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
1996	Merck & Co., Inc.	Merck & Co., Inc.	Eli Lilly and Co.
1997	Merck & Co., Inc.	Merck & Co., Inc.	Eli Lilly and Co.
1998	Merck & Co., Inc.	Merck & Co., Inc.	Eli Lilly and Co.
1999	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.
2000	Merck & Co., Inc.	Merck & Co., Inc.	Merck & Co., Inc.

Notes: We measure R&D leadership using three alternative variables: (a) The number of patent applications, n_{it}, (b) The number of patent citations received from future patents, $\tilde{c}_{it}$, and (c) The number of patent applications weighted by the number of citations received, $\omega_{it}n_{it}$, where $\omega_{it} = \tilde{c}_{it}/\sum_{k=1}^{T}\tilde{c}_{ik}$. R&D leaders according to definitions 1 and 2 are derived from Table 1 and by definition 3 are determined using the following formulas with $\delta = 15\%$:

Definition 3(a): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is}(1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(b): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is}(1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(c): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is}n_{is}(1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Table 3c. R&D leader firms according to definitions 1, 2 and 3 of R&D leadership over 1979-2000

C. Computers

year	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it}n_{it}$
Definition 1			
1979-2000	IBM Co.	IBM Co.	IBM Co.
Definition 2			
1979-2000	IBM Co.	IBM Co.	IBM Co.
1979-2000	Xerox Co.	Xerox Co.	Xerox Co.
1979-2000	Hewlett-Packard Co.	Hewlett-Packard Co.	Hewlett-Packard Co.
1979-2000			Sun Microsystems, Inc.
Definition 3			
1979	IBM Co.	IBM Co.	IBM Co.
1980	IBM Co.	IBM Co.	IBM Co.
1981	IBM Co.	IBM Co.	IBM Co.
1982	IBM Co.	IBM Co.	IBM Co.
1983	IBM Co.	IBM Co.	IBM Co.
1984	IBM Co.	IBM Co.	IBM Co.
1985	IBM Co.	IBM Co.	IBM Co.
1986	IBM Co.	IBM Co.	IBM Co.
1987	IBM Co.	IBM Co.	IBM Co.
1988	IBM Co.	IBM Co.	IBM Co.
1989	IBM Co.	IBM Co.	IBM Co.
1990	IBM Co.	IBM Co.	IBM Co.
1991	IBM Co.	IBM Co.	IBM Co.
1992	IBM Co.	IBM Co.	IBM Co.
1993	IBM Co.	IBM Co.	IBM Co.
1994	IBM Co.	IBM Co.	IBM Co.
1995	IBM Co.	IBM Co.	IBM Co.
1996	IBM Co.	IBM Co.	IBM Co.
1997	IBM Co.	IBM Co.	IBM Co.
1998	IBM Co.	IBM Co.	IBM Co.
1999	IBM Co.	IBM Co.	IBM Co.
2000	IBM Co.	IBM Co.	IBM Co.

Notes: We measure R&D leadership using three alternative variables: (a) The number of patent applications, n_{it}, (b) The number of patent citations received from future patents, $\tilde{c}_{it}$, and (c) The number of patent applications weighted by the number of citations received, $\omega_{it}n_{it}$, where $\omega_{it} = \tilde{c}_{it}/\sum_{k=1}^{T}\tilde{c}_{ik}$. R&D leaders according to definitions 1 and 2 are derived from Table 1 and by definition 3 are determined using the following formulas with $\delta = 15\%$:

Definition 3(a): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is}(1-\delta)^{(t-1)-s} : i = 1,\ldots,N \right\}$$

Definition 3(b): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is}(1-\delta)^{(t-1)-s} : i = 1,\ldots,N \right\}$$

Definition 3(c): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is}n_{is}(1-\delta)^{(t-1)-s} : i = 1,\ldots,N \right\}$$

Table 3d. R&D leader firms according to definitions 1, 2 and 3 of R&D leadership over 1979-2000

D. Software

year	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it} n_{it}$
Definition 1			
1979-2000	Microsoft Co.	Microsoft Co.	Microsoft Co.
Definition 2			
1979-2000	Microsoft Co.	Microsoft Co.	Microsoft Co.
1979-2000	Oracle Co.	Oracle Co.	Oracle Co.
Definition 3			
1979	Atari, Inc.	Atari, Inc.	Atari, Inc.
1980	Atari, Inc.	Atari, Inc.	Atari, Inc.
1981	Atari, Inc.	Atari, Inc.	Atari, Inc.
1982	Atari, Inc.	Atari, Inc.	Atari, Inc.
1983	Atari, Inc.	Atari, Inc.	Atari, Inc.
1984	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Atari, Inc.
1985	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1986	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1987	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1988	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1989	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1990	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1991	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1992	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1993	Wang Laboratories, Inc.	Wang Laboratories, Inc.	Wang Laboratories, Inc.
1994	Microsoft Co.	Microsoft Co.	Wang Laboratories, Inc.
1995	Microsoft Co.	Microsoft Co.	Microsoft Co.
1996	Microsoft Co.	Microsoft Co.	Microsoft Co.
1997	Microsoft Co.	Microsoft Co.	Microsoft Co.
1998	Microsoft Co.	Microsoft Co.	Microsoft Co.
1999	Microsoft Co.	Microsoft Co.	Microsoft Co.
2000	Microsoft Co.	Microsoft Co.	Microsoft Co.

Notes: We measure R&D leadership using three alternative variables: (a) The number of patent applications, n_{it}, (b) The number of patent citations received from future patents, $\tilde{c}_{it}$, and (c) The number of patent applications weighted by the number of citations received, $\omega_{it} n_{it}$, where $\omega_{it} = \tilde{c}_{it} / \sum_{k=1}^{T} \tilde{c}_{ik}$. R&D leaders according to definitions 1 and 2 are derived from Table 1 and by definition 3 are determined using the following formulas with $\delta = 15\%$:

Definition 3(a): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is} (1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(b): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is} (1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(c): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is} n_{is} (1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Table 3e. R&D leader firms according to definitions 1, 2 and 3 of R&D leadership over 1979-2000

E. Defense

year	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it} n_{it}$
Definition 1			
1979-2000	Raytheon Co.	Raytheon Co.	Raytheon Co.
Definition 2			
1979-2000	Raytheon Co.	Raytheon Co.	Raytheon Co.
1979-2000	Northrop Co.	Northrop Co.	Northrop Co.
1979-2000	Litton Systems, Inc.	Litton Systems, Inc.	Litton Systems, Inc.
Definition 3			
1979	Raytheon Co.	Raytheon Co.	Raytheon Co.
1980	Raytheon Co.	Raytheon Co.	Raytheon Co.
1981	Raytheon Co.	Raytheon Co.	Raytheon Co.
1982	Raytheon Co.	Raytheon Co.	Raytheon Co.
1983	Raytheon Co.	Raytheon Co.	Raytheon Co.
1984	Raytheon Co.	Raytheon Co.	Raytheon Co.
1985	Raytheon Co.	Raytheon Co.	Raytheon Co.
1986	Raytheon Co.	Raytheon Co.	Raytheon Co.
1987	Raytheon Co.	Raytheon Co.	Raytheon Co.
1988	Raytheon Co.	Raytheon Co.	Raytheon Co.
1989	Raytheon Co.	Raytheon Co.	Raytheon Co.
1990	Raytheon Co.	Raytheon Co.	Raytheon Co.
1991	Raytheon Co.	Raytheon Co.	Raytheon Co.
1992	Raytheon Co.	Raytheon Co.	Raytheon Co.
1993	Raytheon Co.	Raytheon Co.	Raytheon Co.
1994	Raytheon Co.	Raytheon Co.	Litton Systems, Inc.
1995	Raytheon Co.	Raytheon Co.	Litton Systems, Inc.
1996	Raytheon Co.	Raytheon Co.	Northrop Co.
1997	Raytheon Co.	Raytheon Co.	Northrop Co.
1998	Raytheon Co.	Raytheon Co.	Northrop Co.
1999	Raytheon Co.	Raytheon Co.	Northrop Co.
2000	Raytheon Co.	Raytheon Co.	Northrop Co.

Notes: We measure R&D leadership using three alternative variables: (a) The number of patent applications, n_{it}, (b) The number of patent citations received from future patents, $\tilde{c}_{it}$, and (c) The number of patent applications weighted by the number of citations received, $\omega_{it} n_{it}$, where $\omega_{it} = \tilde{c}_{it} / \sum_{k=1}^{T} \tilde{c}_{ik}$. R&D leaders according to definitions 1 and 2 are derived from Table 1 and by definition 3 are determined using the following formulas with $\delta = 15\%$:

Definition 3(a): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is}(1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(b): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is}(1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(c): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is} n_{is}(1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Table 3f. R&D leader firms according to definitions 1, 2 and 3 of R&D leadership over 1979-2000

F. Oil

year	(a) n_{it}	(b) $\tilde{c}_{it}$	(c) $\omega_{it} n_{it}$
Definition 1			
1979-2000	Exxon Co.	Exxon Co.	Mobil Oil Co.
Definition 2			
1979-2000	Exxon Co.	Exxon Co.	Exxon Co.
1979-2001	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1979-2002	Shell Oil Co.	Shell Oil Co.	Shell Oil Co.
1979-2003	Phillips Petroleum Co.	Phillips Petroleum Co.	Phillips Petroleum Co.
1979-2004	Texaco, Inc.	Texaco, Inc.	Texaco, Inc.
1979-2005	Chevron Research Co.	Chevron Research Co.	Chevron Research Co.
1979-2006	Atlantic Richfield Co.	Atlantic Richfield Co.	Atlantic Richfield Co.
Definition 3			
1979	Exxon Co.	Mobil Oil Co.	Philliphs Petroleum Co.
1980	Exxon Co.	Mobil Oil Co.	Philliphs Petroleum Co.
1981	Philliphs Petroleum Co.	Mobil Oil Co.	Philliphs Petroleum Co.
1982	Exxon Co.	Mobil Oil Co.	Philliphs Petroleum Co.
1983	Mobil Oil Co.	Mobil Oil Co.	Philliphs Petroleum Co.
1984	Mobil Oil Co.	Mobil Oil Co.	Philliphs Petroleum Co.
1985	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1986	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1987	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1988	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1989	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1990	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1991	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1992	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1993	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1994	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1995	Mobil Oil Co.	Mobil Oil Co.	Mobil Oil Co.
1996	Mobil Oil Co.	Exxon Co.	Mobil Oil Co.
1997	Exxon Co.	Exxon Co.	Mobil Oil Co.
1998	Exxon Co.	Exxon Co.	Exxon Co.
1999	Exxon Co.	Exxon Co.	Exxon Co.
2000	Exxon Co.	Exxon Co.	Exxon Co.

Notes: We measure R&D leadership using three alternative variables: (a) The number of patent applications, n_{it}, (b) The number of patent citations received from future patents, $\tilde{c}_{it}$, and (c) The number of patent applications weighted by the number of citations received, $\omega_{it} n_{it}$, where $\omega_{it} = \tilde{c}_{it} / \sum_{k=1}^{T} \tilde{c}_{ik}$. R&D leaders according to definitions 1 and 2 are derived from Table 1 and by definition 3 are determined using the following formulas with $\delta = 15\%$:

Definition 3(a): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} n_{is} (1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(b): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \tilde{c}_{is} (1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Definition 3(c): $$\text{R\&D leader}(t;\delta) = \arg\max_i \left\{ \sum_{s=1}^{t-1} \omega_{is} n_{is} (1-\delta)^{(t-1)-s} : i = 1, \ldots, N \right\}$$

Table 4a. PVAR-X estimates for the aircrafts industry

Definition 1(a)(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.08	0.05	-0.13
λ_{t-1}^o	0.09	0.78	0.31
λ_{t-1}^*	0.07	0.01	0.85
eig	0.88		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.20	0.07
λ_t^o	-0.20	1.04	0.01
λ_t^*	0.07	0.01	1.01

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	-0.35	-0.24	-0.31

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.69	0.26	0.73

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.48	-0.19	-0.11

Definition 1(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.09	0.05	-0.09
λ_{t-1}^o	0.18	0.79	0.22
λ_{t-1}^*	0.01	0.00	0.84
eig	0.84		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.13	0.04
λ_t^o	-0.13	1.02	0.02
λ_t^*	0.04	0.02	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.04	0.08	-0.04

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.04	0.09	0.02

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.36	-0.23	-0.06

Definition 2(a)(b)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.01	-0.08	0.00
λ_{t-1}^o	0.18	0.79	0.23
λ_{t-1}^*	0.01	0.00	0.84
eig	0.82		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.13	0.04
λ_t^o	-0.13	1.02	0.02
λ_t^*	0.04	0.02	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.04	0.08	-0.03

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.05	0.09	0.04

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.30	-0.19	-0.08

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 1(a)(b):* Honeywell, Inc.
- *Definition 1(c):* Allied-Signal Co.
- *Definition 2(a)(b)(c):* Honeywell, Inc., United Technologies Co., Allied-Signal Co.

Table 4a (continued). PVAR-X estimates for the aircrafts industry

Definition 3(a)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.06	0.05	-0.13
λ_{t-1}^o	0.02	0.77	0.30
λ_{t-1}^*	0.08	0.00	0.83
eig	0.85		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.22	0.05
λ_t^o	-0.22	1.05	0.02
λ_t^*	0.05	0.02	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	-0.07	-0.13	-0.03

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.26	-0.12	0.37

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.38	-0.26	0.01

Definition 3(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.12	0.04	-0.12
λ_{t-1}^o	0.15	0.81	0.25
λ_{t-1}^*	0.08	0.00	0.83
eig	0.86		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.05	0.06
λ_t^o	-0.05	1.00	0.03
λ_t^*	0.06	0.03	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.00	-0.05	-0.05

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.44	0.75	-0.05

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.57	-0.29	0.03

Definition 3(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.08	0.05	-0.11
λ_{t-1}^o	0.19	0.80	0.23
λ_{t-1}^*	0.04	0.00	0.84
eig	0.85		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.11	0.04
λ_t^o	-0.11	1.01	0.02
λ_t^*	0.04	0.02	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.02	-0.02	0.00

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.44	0.33	-0.10

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.55	-0.29	-0.05

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 3(a)(b)(c):* The evolution of R&D leaders over 1979-2000 can be seen in Table 3a.

Table 4b. PVAR-X estimates for the pharmaceuticals industry

Definition 1(a)(b)(c), 3(a)(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.05	0.05	0.10
λ_{t-1}^o	0.14	0.78	0.19
λ_{t-1}^*	0.00	-0.02	0.97
eig	0.94		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.05	0.00
λ_t^o	0.05	1.00	0.02
λ_t^*	0.00	0.02	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.15	0.17	-0.24

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.90	-0.41	-0.33

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.26	0.46	0.05

Definition 2(a)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.05	0.03	0.05
λ_{t-1}^o	0.12	0.74	0.14
λ_{t-1}^*	0.00	-0.02	0.97
eig	0.96		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.04	0.00
λ_t^o	0.04	1.00	0.01
λ_t^*	0.00	0.01	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.05	0.06	-0.04

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.12	0.65	-0.06

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.47	0.72	-0.04

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 1(a)(b)(c), 3(a)(b):* Merck & Co., Inc.
- *Definition 2(a)(c):* Merck & Co., Inc., Eli Lilly and Co., Pfizer, Inc., Abbott Laboratories

Table 4b (continued). PVAR-X estimates for the pharmaceuticals industry

Definition 2(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.05	0.03	0.05
λ_{t-1}^o	0.12	0.74	0.09
λ_{t-1}^*	0.00	-0.02	0.96
eig	0.95		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.03	0.00
λ_t^o	0.03	1.00	0.01
λ_t^*	0.00	0.01	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.01	0.00	-0.02

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.14	0.64	0.06

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.48	0.79	0.01

Definition 3(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.04	0.08	0.12
λ_{t-1}^o	0.14	0.79	0.16
λ_{t-1}^*	0.00	-0.01	0.97
eig	0.95		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.05	0.01
λ_t^o	0.05	1.00	0.02
λ_t^*	0.01	0.02	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.13	0.01	-0.02

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.12	-0.07	-0.20

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.50	0.48	-0.01

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 2(b):* Merck & Co., Inc., Eli Lilly and Co., Pfizer, Inc., Abbott Laboratories, Warner-Lambert Co., Johnson & Johnson
- *Definition 3(c):* The evolution of R&D leaders over 1979-2000 can be seen in Table 3b.

Table 4c. PVAR-X estimates for the computers industry

Definition 1(a)(b)(c), 3(a)(b)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.03	0.03	0.01
λ_{t-1}^o	0.10	0.86	0.13
λ_{t-1}^*	0.02	-0.01	0.90
eig	0.89		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.01	0.03
λ_t^o	0.01	1.00	0.01
λ_t^*	0.03	0.01	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.01	-0.01	-0.04

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.69	0.97	-0.22

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.57	0.38	-0.04

Definition 2(a)(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.03	0.01	-0.01
λ_{t-1}^o	0.09	0.85	0.14
λ_{t-1}^*	0.02	-0.01	0.91
eig	0.88		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.01	0.03
λ_t^o	0.01	1.00	0.01
λ_t^*	0.03	0.01	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.01	0.00	-0.05

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.67	1.07	-0.33

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.55	0.29	0.00

Definition 2(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.03	0.01	0.01
λ_{t-1}^o	0.09	0.84	0.15
λ_{t-1}^*	0.02	-0.01	0.91
eig	0.88		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.01	0.03
λ_t^o	0.01	1.00	0.01
λ_t^*	0.03	0.01	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.04	0.07	-0.10

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.32	1.12	-0.13

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.45	0.28	0.00

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 1(a)(b)(c), 3(a)(b)(c):* IBM Co.
- *Definition 2(a)(b):* IBM Co., Xerox Co., Hewlett-Packard Co.
- *Definition 2(c):* IBM Co., Xerox Co., Hewlett-Packard Co., Sun Microsystems, Inc.

Table 4d. PVAR-X estimates for the software industry

Definition 1(a)(b)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.00	0.04	0.01
λ_{t-1}^o	-0.02	0.84	0.32
λ_{t-1}^*	0.00	-0.01	0.99
eig	0.95		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.09	0.00
λ_t^o	0.09	1.01	0.00
λ_t^*	0.00	0.00	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.02	0.09	-0.10

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	1.23	0.43	-0.62

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.45	0.26	-0.10

Definition 2(a)(b)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.00	0.03	0.01
λ_{t-1}^o	-0.01	0.84	0.24
λ_{t-1}^*	0.00	-0.02	0.97
eig	0.93		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.09	0.00
λ_t^o	0.09	1.00	0.00
λ_t^*	0.00	0.00	1.00

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.01	0.10	-0.04

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	1.19	0.35	-0.36

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.43	0.10	-0.04

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 1(a)(b)(c):* Microsoft Co.
- *Definition 2(a)(b)(c):* Microsoft Co., Oracle Co.

Table 4d (continued). PVAR-X estimates for the software industry

Definition 3(a)(b)

Own effects

ζ	y_t	λ^o_t	λ^*_t
y_{t-1}	0.00	0.05	0.03
λ^o_{t-1}	0.00	0.86	0.34
λ^*_{t-1}	0.01	0.00	0.95
eig	0.94		

Ω_ϵ	y_t	λ^o_t	λ^*_t
y_t	1.00	0.10	0.00
λ^o_t	0.10	1.01	0.00
λ^*_t	0.00	0.00	1.00

Leaders' effects

ζ^o_L	y_t	λ^o_t	λ^*_t
λ^o_{Lt-1}	0.02	0.08	-0.05

ζ^*_L	y_t	λ^o_t	λ^*_t
λ^*_{Lt-1}	0.04	0.28	-0.04

Stock market effects

β	y_t	λ^o_t	λ^*_t
$\overline{y}_t$	0.28	0.32	-0.04

Definition 3(c)

Own effects

ζ	y_t	λ^o_t	λ^*_t
y_{t-1}	0.00	0.05	0.02
λ^o_{t-1}	-0.01	0.86	0.30
λ^*_{t-1}	0.01	0.00	0.93
eig	0.90		

Ω_ϵ	y_t	λ^o_t	λ^*_t
y_t	1.00	0.10	0.00
λ^o_t	0.10	1.01	0.00
λ^*_t	0.00	0.00	1.00

Leaders' effects

ζ^o_L	y_t	λ^o_t	λ^*_t
λ^o_{Lt-1}	0.02	0.08	-0.03

ζ^*_L	y_t	λ^o_t	λ^*_t
λ^*_{Lt-1}	-0.03	0.02	0.01

Stock market effects

β	y_t	λ^o_t	λ^*_t
$\overline{y}_t$	0.23	0.11	0.05

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ^o_L and ζ^*_L panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 3(a)(b)(c):* The evolution of R&D leaders over 1979-2000 can be seen in Table 3d.

Table 4e. PVAR-X estimates for the defense industry

Definition 1(a)(b)(c), 3(a)(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.09	0.09	0.03
λ_{t-1}^o	0.28	0.79	0.41
λ_{t-1}^*	0.00	0.00	0.85
eig	0.87		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.16	0.04
λ_t^o	0.16	1.02	0.10
λ_t^*	0.04	0.10	1.01

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	-0.10	0.13	-0.04

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	1.45	-0.52	0.02

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.12	0.21	0.04

Definition 2(a)(b)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.15	0.06	0.09
λ_{t-1}^o	0.25	0.70	0.52
λ_{t-1}^*	-0.02	0.00	0.90
eig	0.90		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.13	0.02
λ_t^o	0.13	1.01	0.09
λ_t^*	0.02	0.09	1.01

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	-0.08	0.09	-0.06

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.30	0.20	-0.12

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.13	0.37	-0.01

Definition 3(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.14	0.01	0.05
λ_{t-1}^o	0.23	0.67	0.59
λ_{t-1}^*	0.00	0.01	0.93
eig	0.95		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.10	0.04
λ_t^o	0.10	1.01	0.09
λ_t^*	0.04	0.09	1.01

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	-0.02	0.19	-0.14

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.22	-0.37	0.04

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.01	0.32	-0.11

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 1(a)(b)(c), 3(a)(b):* Raytheon Co.
- *Definition 2(a)(b)(c):* Raytheon Co., Northrop Co., Litton Systems, Inc.
- *Definition 3(c):* The evolution of R&D leaders over 1979-2000 can be seen in Table 3e.

Table 4f. PVAR-X estimates for the oil industry

Definition 1(a)(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.01	0.00	0.00
λ_{t-1}^o	0.01	0.91	0.00
λ_{t-1}^*	0.05	-0.02	0.99
eig	0.99		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.02	0.03
λ_t^o	-0.02	1.00	0.26
λ_t^*	0.03	0.26	1.07

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.04	0.11	0.12

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.89	-0.98	0.47

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.04	0.24	0.05

Definition 1(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.02	0.00	0.02
λ_{t-1}^o	-0.02	0.90	0.02
λ_{t-1}^*	0.08	-0.02	0.99
eig	0.99		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.01	0.00
λ_t^o	-0.01	1.00	0.26
λ_t^*	0.00	0.26	1.07

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.15	0.34	0.12

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.05	-0.18	0.13

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	-0.02	0.14	0.03

Definition 2(a)(b)(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.01	0.00	0.01
λ_{t-1}^o	0.00	0.90	0.02
λ_{t-1}^*	0.06	-0.03	0.99
eig	0.98		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.02	0.01
λ_t^o	-0.02	1.00	0.26
λ_t^*	0.01	0.26	1.07

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.01	-0.01	0.03

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	-0.02	-0.02	0.06

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.02	0.02	0.08

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 1(a)(b):* Exxon Co.
- *Definition 1(c):* Mobil Oil Co.
- *Definition 2(a)(b)(c):* Exxon Co., Mobil Oil Co., Shell Oil Co., Phillips Petroleum Co., Texaco, Inc., Chevron Research Co., Atlantic Richfield Co.

Table 4f (continued). PVAR-X estimates for the oil industry

Definition 3(a)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	0.00	0.00	0.01
λ_{t-1}^o	0.00	0.90	0.01
λ_{t-1}^*	0.06	-0.03	0.99
eig	0.99		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.02	-0.01
λ_t^o	-0.02	1.00	0.26
λ_t^*	-0.01	0.26	1.07

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.09	0.02	0.01

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.06	-0.02	0.13

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	-0.06	0.17	0.01

Definition 3(b)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.01	-0.01	0.02
λ_{t-1}^o	-0.01	0.90	0.02
λ_{t-1}^*	0.10	-0.02	0.99
eig	0.99		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	-0.03	-0.01
λ_t^o	-0.03	1.00	0.27
λ_t^*	-0.01	0.27	1.07

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.12	0.39	-0.07

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.05	-0.10	0.23

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.01	0.30	0.02

Definition 3(c)

Own effects

ζ	y_t	λ_t^o	λ_t^*
y_{t-1}	-0.01	-0.01	0.02
λ_{t-1}^o	-0.03	0.90	0.02
λ_{t-1}^*	0.06	-0.03	0.99
eig	0.99		

Ω_ϵ	y_t	λ_t^o	λ_t^*
y_t	1.00	0.00	0.00
λ_t^o	0.00	1.00	0.26
λ_t^*	0.00	0.26	1.07

Leaders' effects

ζ_L^o	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^o	0.07	0.20	-0.01

ζ_L^*	y_t	λ_t^o	λ_t^*
λ_{Lt-1}^*	0.01	-0.18	0.11

Stock market effects

β	y_t	λ_t^o	λ_t^*
$\overline{y}_t$	0.00	0.18	0.03

Notes: Estimation results of the following specification are reported for various definitions of D_{Ljt}:

$$\tilde{X}_{it} = a_i + \zeta \tilde{X}_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

with

$$\tilde{X}_{it} = X_{it} - \beta \overline{y}_t - \sum_{j \neq i} \zeta_L X_{jt-1} D_{Ljt}.$$

The eig figure denotes the maximum of the absolute value or modulus of the eigenvalues of the ζ matrix. This value should be inside the unite circle for the covariance stationarity of the PVAR(1) model. The estimates of Ω_a, Ω_0 are not reported in the table. The elements of the ζ_L matrix are reorganized into the ζ_L^o and ζ_L^* panels. The R&D leaders for different definitions of D_{Ljt} are the next companies:

- *Definition 3(a)(b)(c):* The evolution of R&D leaders over 1979-2000 can be seen in Table 3f.

Figure 1. Application-grant lag empirical distribution. *Notes:* Cumulative distribution of the time duration between the patent application date and the publication date measured in years. The distribution is computed using the application-grant lag of patents, which were submitted to the U.S. Patent Office in 1997. (This year is practically not affected by sample truncation bias.)

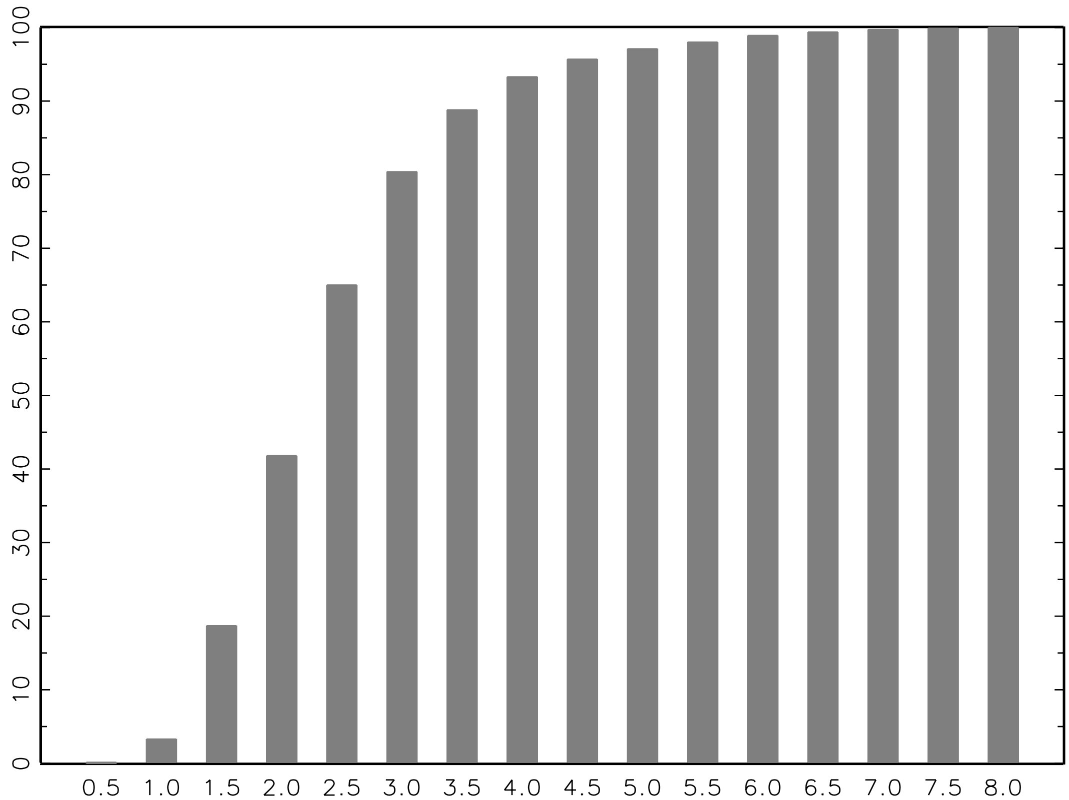

Figure 2. Citation lag empirical distribution. *Notes:* Cumulative distribution of the time duration between the publication dates of citing and cited patents measured in years.

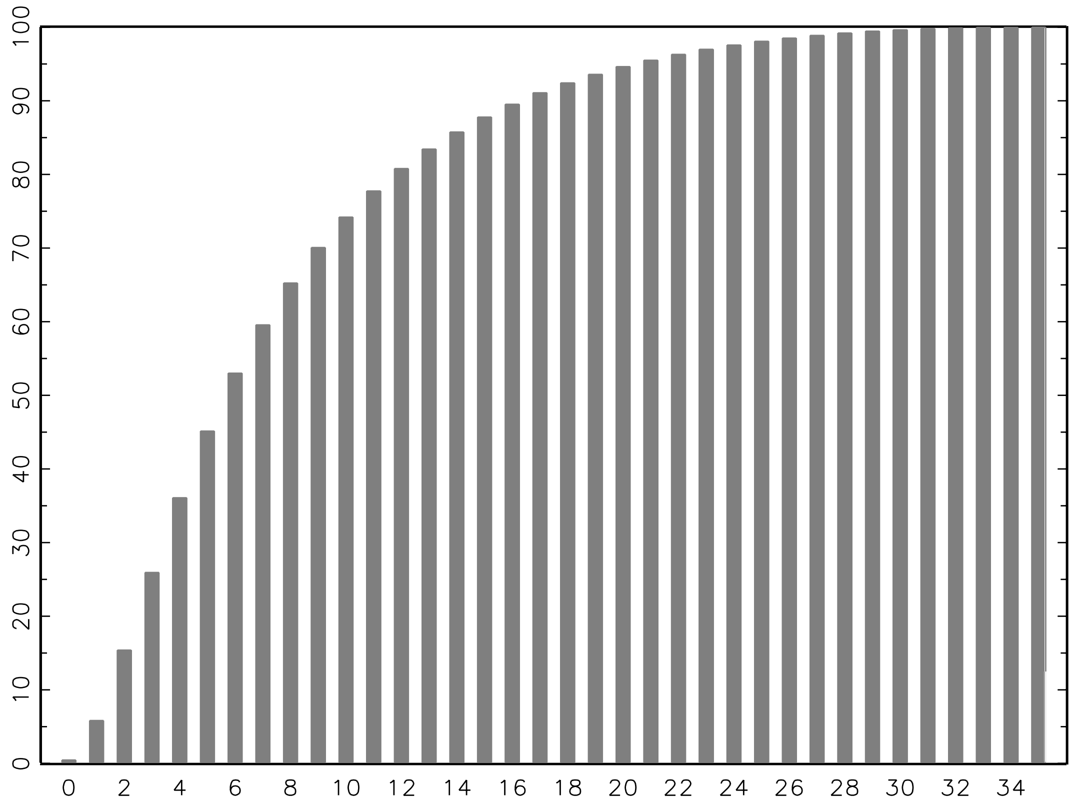

Figure 3. Average number of citations that patents receive from future patents by technological category during the 1979-2005 period.

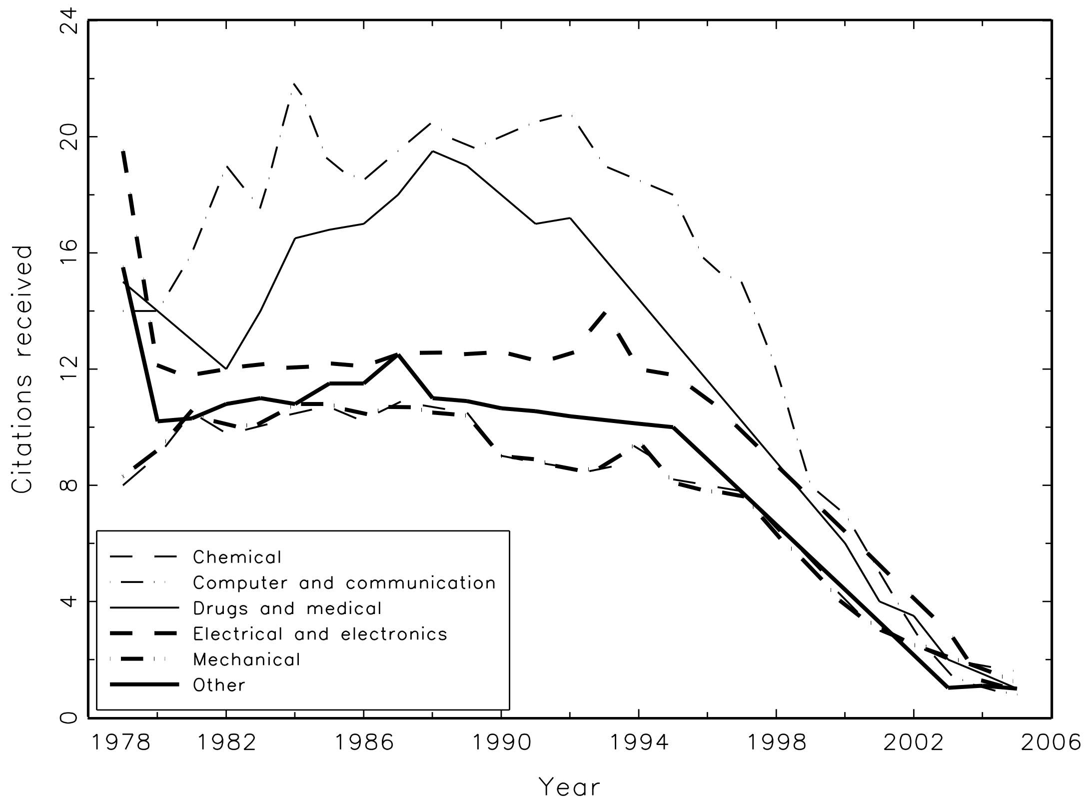

Figure 4. Average number of citations received corrected for sample truncation bias. *Notes:* The *fixed effects* approach of Hall et al (2001) is used. That is for each patent we divide the number of citations received from future patents by the average number of patent citations received in the corresponding technological category and year.

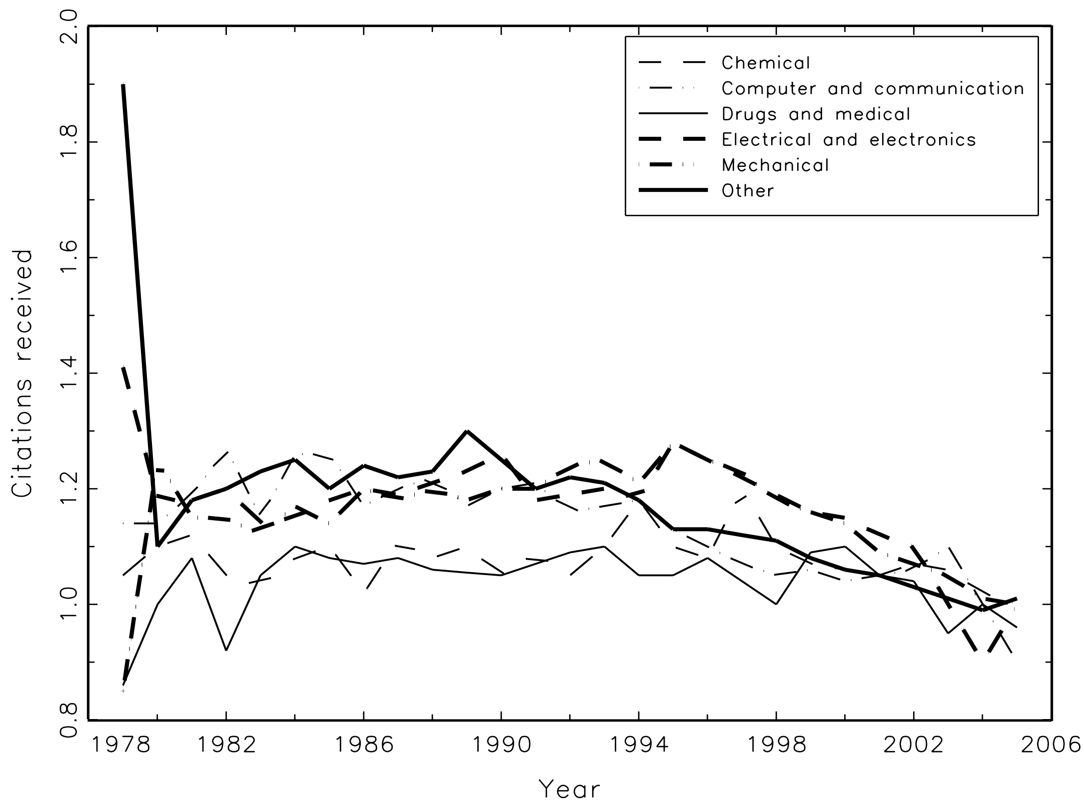

Figure 5. Average quality of knowledge that firms receive from past patents by citing them in the patent documents. *Notes:* Patent citations are classified as (1) self-citations, (2) intra-industry citations and (3) inter-industry citations. The quality of knowledge is measured by the number of citations received from future patents (corrected for sample truncation bias). Firms are classified into two sectors: (1) non-hi-tech (others) and (2) hi-tech. (Hall and Mairesse, 1996)

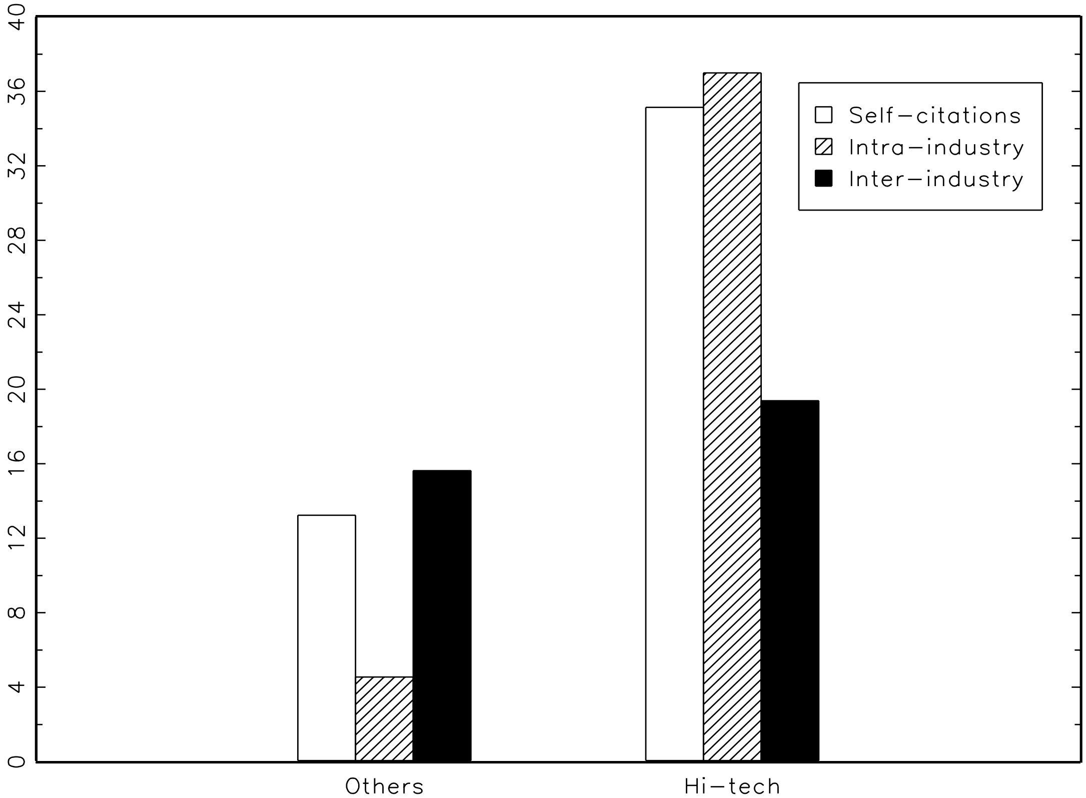

Figure 6. Average quality of knowledge that firms receive from past patents by citing them in the patent documents. *Notes:* Patent citations are classified as (1) self-citations, (2) intra-industry citations and (3) inter-industry citations. The quality of knowledge is measured by the number of citations received from future patents (corrected for sample truncation bias). Firms are classified into the following 16 industries: (1) paper and printing, (2) chemicals, (3) rubber and plastics, (4) wood and misc., (5) primary metals, (6) fabricated metals, (7) machinery, (8) electrical machinery, (9) autos, (10) aircrafts and other trans., (11) textiles and leather, (12) pharmaceuticals, (13) food, (14) computers and inst., (15) oil, (16) non-manufacturing. (Hall and Mairesse, 1996)

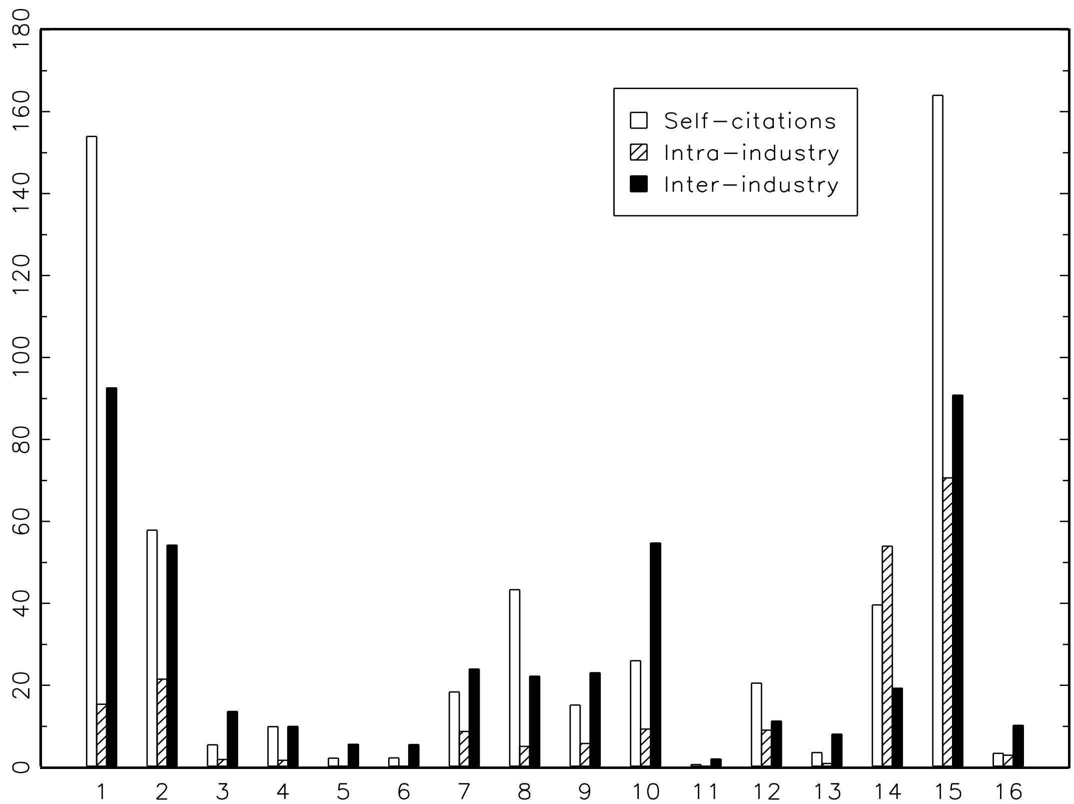

Figure 7. Evolution of patent applications counts for six industries. *Notes:* The figure shows the evolution of $\left[\sum_{i=1}^{N} n_{it}\right]$ for each industry over 1979-2000.

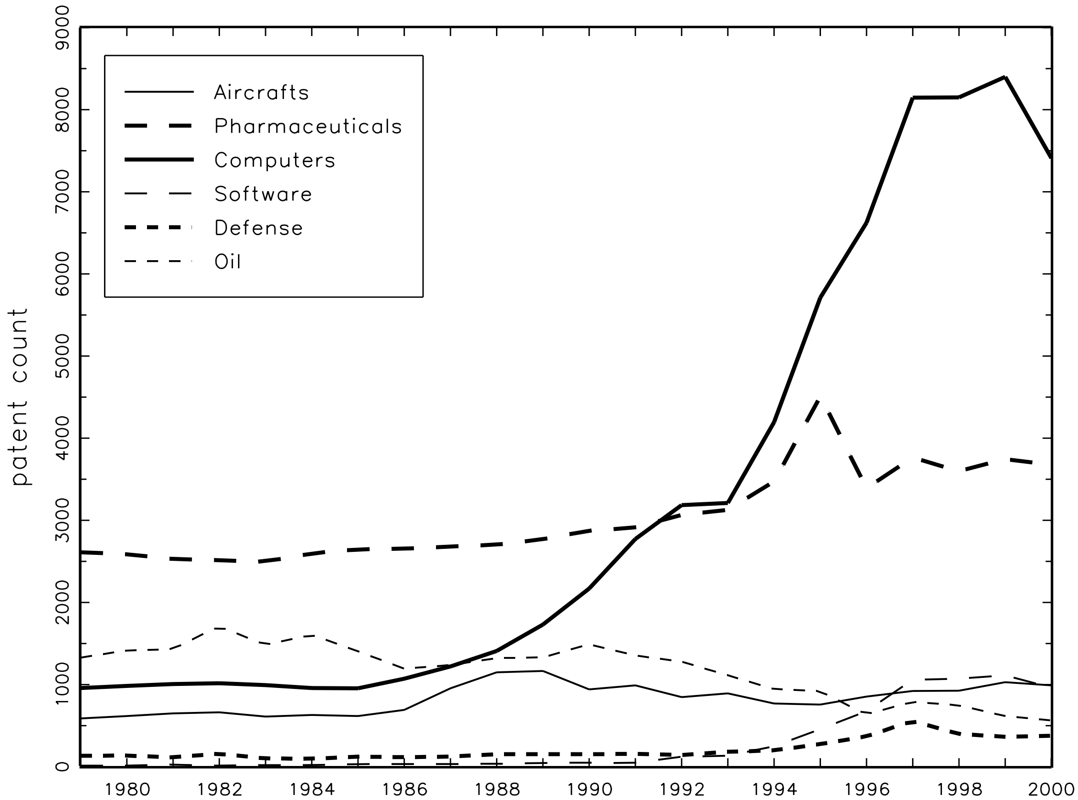

Figure 8. Evolution of log patent applications counts for six industries. *Notes:* The figure shows the evolution of $\left[\ln \sum_{i=1}^{N} n_{it}\right]$ for each industry over 1979-2000.

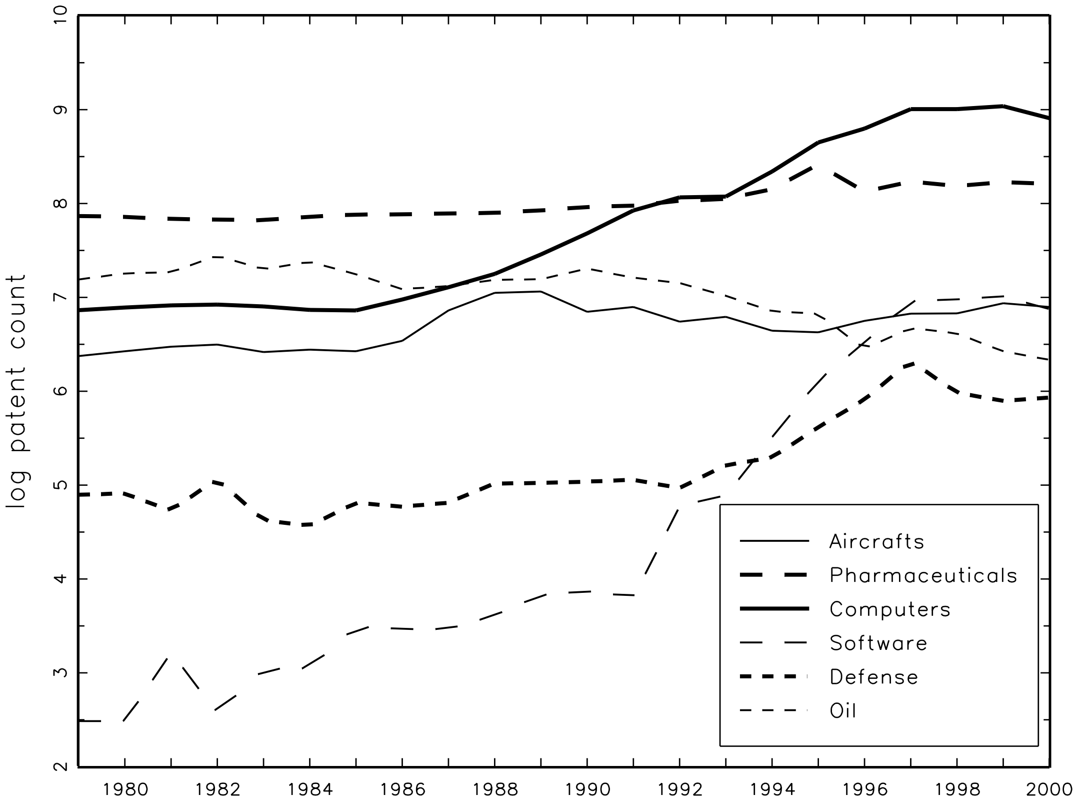

Figure 9. Evolution of observable and latent patent intensity components in the aircrafts industry.
Notes: The figure shows the evolution of $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{o}\right]$ and $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{*}\right]$ over 1979-2000.

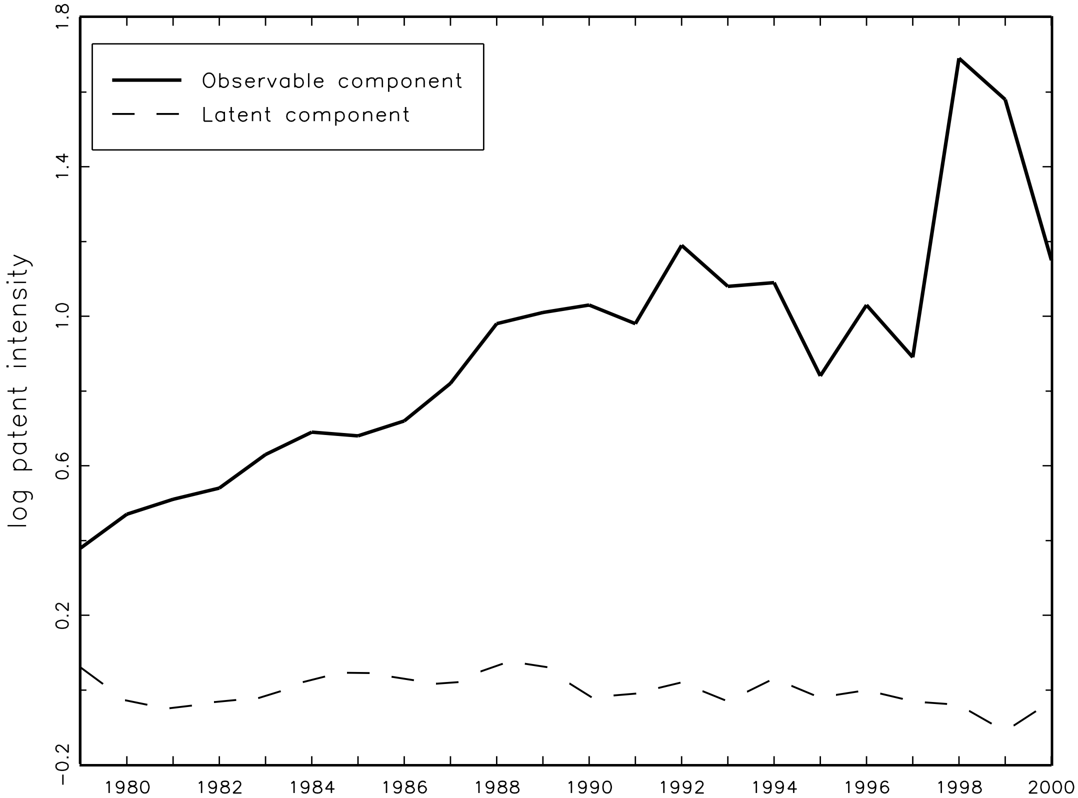

Figure 10. Evolution of observable and latent patent intensity components in the pharmaceuticals industry. *Notes:* The figure shows the evolution of $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{o}\right]$ and $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{*}\right]$ over 1979-2000.

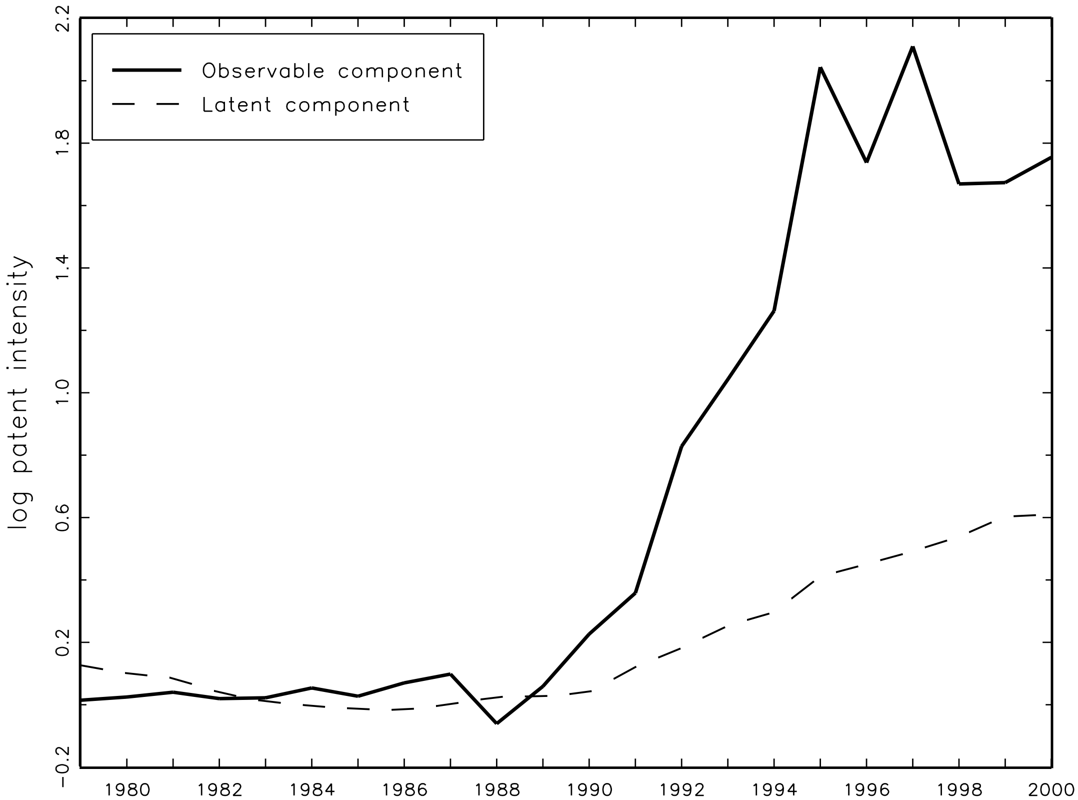

Figure 11. Evolution of observable and latent patent intensity components in the computers industry.
Notes: The figure shows the evolution of $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{o}\right]$ and $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{*}\right]$ over 1979-2000.

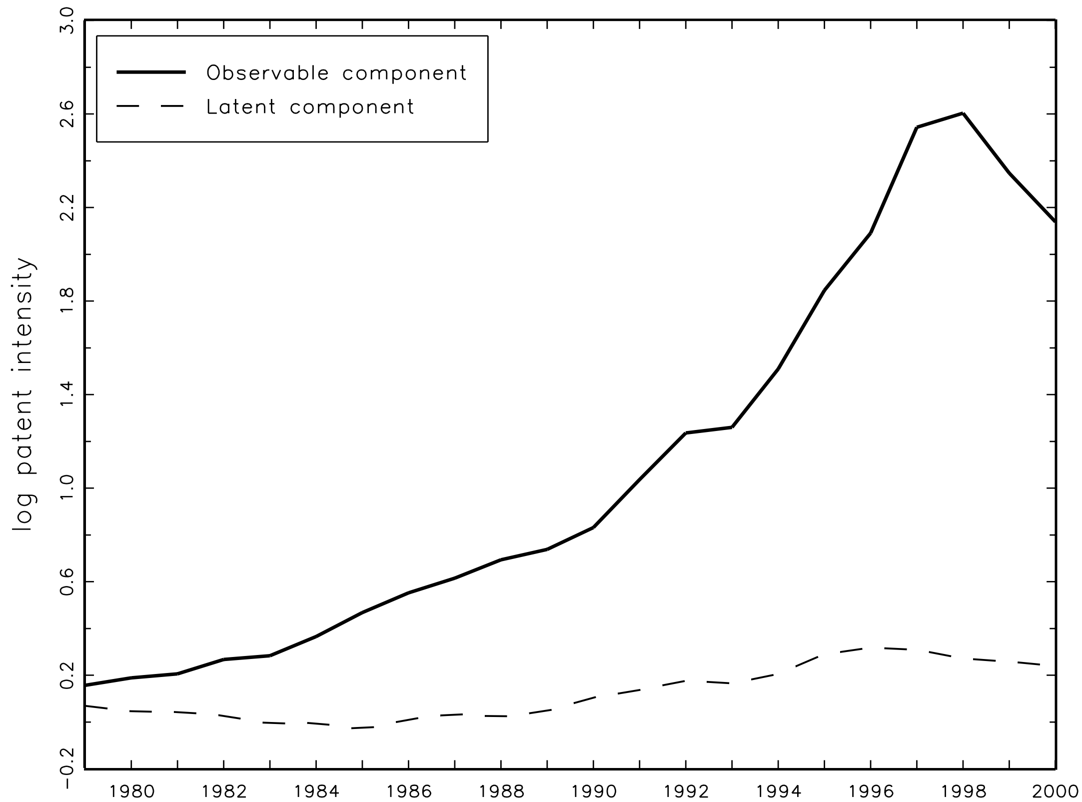

Figure 12. Evolution of observable and latent patent intensity components in the software industry.
Notes: The figure shows the evolution of $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{o}\right]$ and $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{*}\right]$ over 1979-2000.

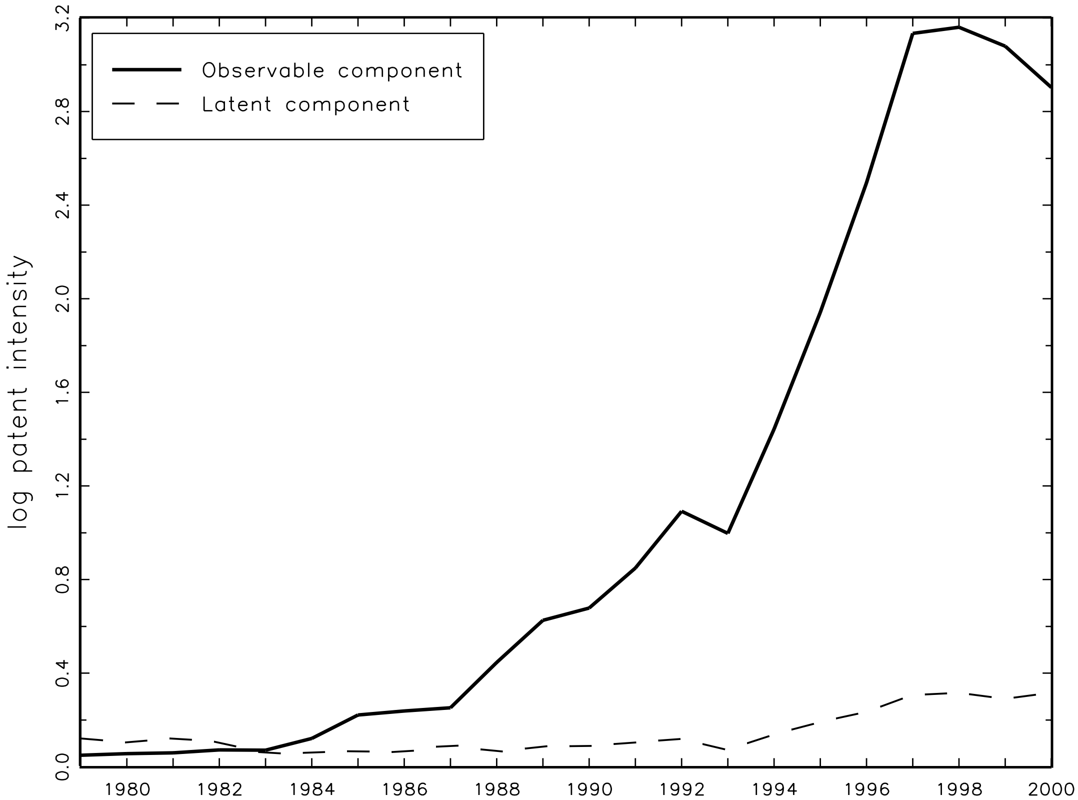

Figure 13. Evolution of observable and latent patent intensity components in the defense industry. *Notes:* The figure shows the evolution of $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{o}\right]$ and $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{*}\right]$ over 1979-2000.

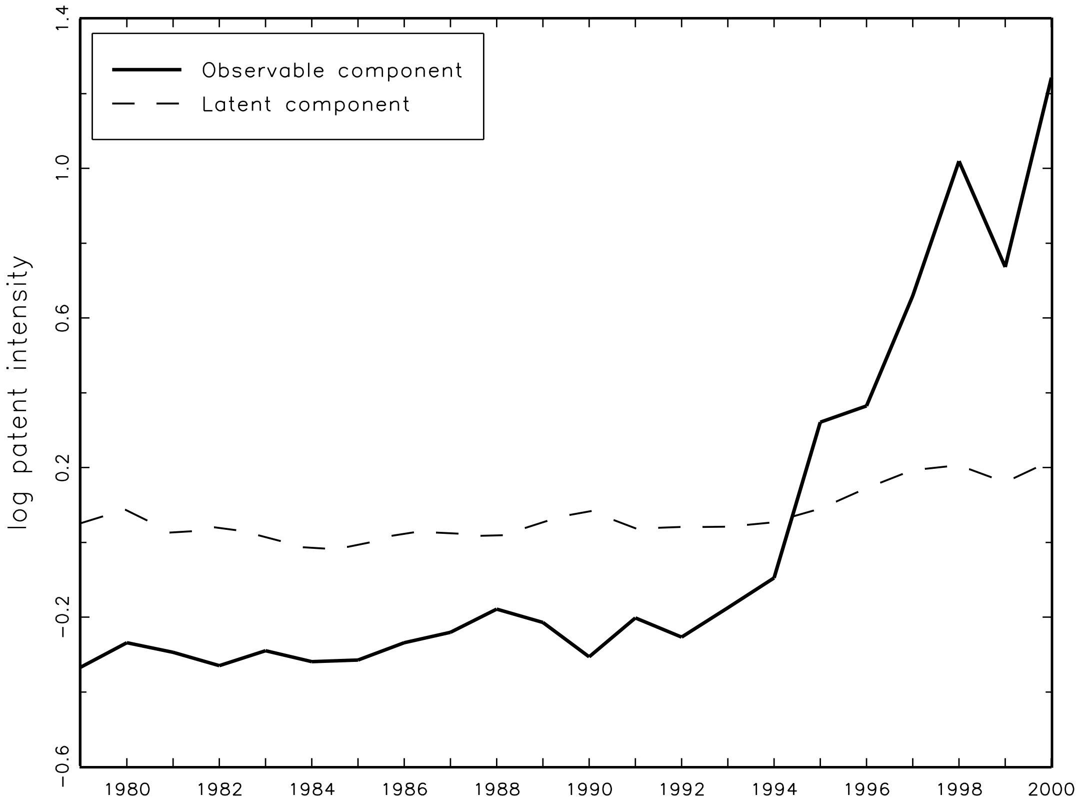

Figure 14. Evolution of observable and latent patent intensity components in the oil industry. *Notes:* The figure shows the evolution of $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{o}\right]$ and $\left[(1/N)\sum_{i=1}^{N}\ln\hat{\lambda}_{it}^{*}\right]$ over 1979-2000.