Technology Centrality and Stock Market Valuation of Innovations*

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Abstract

We investigate the stock market valuation of firm innovations by developing a general-equilibrium quality-ladder growth model with technological interdependence across sectors. Our model highlights the importance of the technology centrality, which captures the position of a sector in the technology network. Innovations in sectors with greater technology centrality benefit more from knowledge spillovers and are shown endogenously more valuable. We adopt an event study approach, which relies on the stock market response to the announcement of patent grants, to empirically estimate the economic value of patents and a comprehensive patent citation database to construct a measure of technology centrality. We find that a 1% increase in the technology centrality of a sector raises the average value of patents in that sector by 0.1%.

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1. Introduction

Innovation has long been considered the primary driver of a company's growth and is therefore a key focus of the stock market. Economists, in turn, use the stock market to evaluate the value of innovations.[1] Past empirical studies document a substantial difference in the stock market valuation of patents filed in different technology sectors. For example, Hall et al. (2005) show that the market premium of patent yield for Drugs is three times as large as the average effect and that of Computers is twice as high. Chen et al. (2019) compare the estimated market value of FinTech innovations with other financial innovations and show that the median value of a FinTech innovation is more than 10 times higher than that of the latter. However, an important question remains untackled: What drives the aforementioned differences in innovation values across different technology sectors? In this paper, we aim to provide one of the first attempts to address this question by exploring the role that a sector's technological position plays in affecting the value of innovations.

Innovations rarely occur independently of each other. Knowledge accumulation in a sector contributes to innovations not only in its own sector but also in neighboring sectors, and the latter generates further knowledge spillovers to peripheral sectors.[2] Consequently, a new innovation benefits from previous innovations in the entire technology network. Innovations located in the central position of the technology network can draw on a wider range of knowledge stocks and potentially are of higher quality.

To provide a conceptual framework for our analysis, we build a quality-ladder innovation model with multiple technology sectors. Our model features both intrasectoral and intersectoral knowledge spillovers. In this model, the economy is represented by a technology network that captures the topology of knowledge flows from one sector to another. A sector's knowledge stock benefits future innovation

[1]See, for example, Hall (1999); Hall et al. (2005); Kogan et al. (2017).

[2]For instance, Acemoglu et al. (2016) show that a 10% increase in upstream innovation corresponds to a 3.5% increase in forward patenting.

activities in the neighboring sectors directly and the peripheral sectors indirectly through the network. A firm enters a sector by incurring research expenses to conduct innovation. When a firm innovates successfully, it applies for a patent, according to which a generic product is designed. The firm draws on past knowledge accumulations from different sectors when designing the new product, which improves the quality of existing products. We show that the extent of quality improvement, and thus the profit, of new innovations in a sector is determined by its technology centrality, which captures the position of the sector in the technology network. The more central the position in which a sector is located, the stronger innovations in the sector benefit from knowledge spillovers, and the higher the values of innovations. In equilibrium, the free-entry condition equalises the cost of innovations and the expected value across sectors. Therefore, innovations of higher values are also more expensive to produce.

Our model provides a useful guidance for empirical analyses. We first follow Kogan et al. (2017) to use an event study method, which relies on the responses of the stock market to the announcement of corporate patenting activities, to measure the economic value of innovations. This method is particularly suitable for our analysis as it offers a market valuation for every patent granted to a firm. We then use a comprehensive patent database (PATSTAT Global), that contains detailed information of patent citations, to construct a matrix capturing the technological connections between sectors in the economy. We proceed to calculate the dominant right eigenvector centrality for each sector in the network, which is the empirical counterpart of the technology centrality in our model. With the constructed measure of technology centrality, the relationship between technology centrality and innovation values is examined in various model specifications. The empirical results provide strong evidence for the importance of sectors' technology centrality. We find a positive and significant correlation between innovation values and technology centrality. A 1% increase of technology centrality raises the average value of innovations by 0.1%.

We also investigate the relationship between the cost of innovations and firms' technology centrality. Our model implies a higher innovation cost for firms conducting innovations in sectors with higher centrality. We thus construct a measure of a firm's technology centrality, which reflects the weighted centrality of the firm's patent portfolio, with weights equal to the sectoral shares of patents granted to a firm in a given year. A regression of firms' R&D expenses over the technology centrality of their patent portfolios is implemented. We find consistent evidence of positive and statistically significant relationship between firms' technology centrality and their R&D expenses, with the results robust to alternative measures of the dependent and independent variables.

Our paper contributes to several strands of literature. First, our analyses build upon the literature that uses stock price data to investigate the value of innovation (see, e.g., Pakes (1985), Austin (1993), Hall et al. (2005), Nicholas (2008), Kogan et al. (2017), Chen et al. (2019), and Kelly et al. (2021)). Hall et al. (2005) document substantial differences in the market value of patents in broadly defined technology sectors. Chen et al. (2019) focus on FinTech innovations and show the existence of market premium of FinTech innovations over other financial innovations. All previous studies analyze the value of innovations in different technology fields independently and ignore the potential role that intersectoral technological connections play in driving the difference of patent values across sectors.[3] By the contrary, our paper establishes a theoretical connection between the structure of the technology network and the value of patents, and provides novel evidence to support this finding.

Our paper is also related to the large literature on endogenous growth (See, for example, Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), Aghion et al. (1997), Kortum (1997), Jones (1995), Klette and Kortum (2004), Acemoglu et al. (2018), Cai and Li (2019), Akcigit and Kerr (2018), Huang and Zenou (2020) and Liu and Ma (2021).) Most previous studies focus on a representative sector and ignore the potential heterogeneous intersectoral knowledge spillovers. Our paper extends a quality-ladder innovation model to incorporate a technology network

[3]One exception is Huang and Xie (2023), who use stock price data to assess the value of patents for participants of M&As.

that captures intersectoral knowledge spillovers. In this sense, our model is closest to Liu and Ma (2021), who solve for the optimal allocation of R&D resources in an economy with an interconnected innovation network. In their model, past knowledge accumulations contribute to the arrival rate of new innovations, but the quality improvement of each sector remains independent of the network structure. Our model differs in that the quality improvement, and hence the value of innovations, of each sector depends critically on the network characteristics, which is the key feature of our model that enables us to empirically verify the theoretical relationship between the value of innovations and their network characteristics.

Obviously, our paper also belongs to the growing literature on social, economic and production networks (Ballester et al., 2006; König et al., 2019; Acemoglu et al., 2012; Baqaee, 2018; Acemoglu and Azar, 2020; Elliott et al., 2022). Ballester et al. (2006) propose a measure of a player's centrality reflecting her contribution to the centrality of the others to identify the key players in a network. We obtain a similar finding in the context of the innovation network, which demonstrates that the key innovation sectors in an economy are the ones with high technology centrality.

Lastly, our paper contributes to the literature that explores the impact of technological opportunity on innovative activity (Scherer, 1965, 1967; Pakes and Schankerman, 1984; Levin et al., 1985; Jaffe, 1986, 1989; Cohen and Levinthal, 1989). A finding emerging from the literature is the significant power of opportunity variables representing the sources of extraindustry knowledge to explain the variance in R&D intensity (Levin et al., 1985; Cohen and Levinthal, 1989). Our paper proposes the eigenvector centrality as a sufficient statistic to capture the overall knowledge spillovers from the whole technology network to individual sectors. An advantage of this measure is that it incorporates the information of both the direct intersectoral knowledge spillovers and the indirect ones through intermediate sectors, and thus it serves as a more accurate measure.

The remainder of the paper is structured as follows: Section 2 outlines the innovation model, followed by the introduction of the data in section 3 and empirical analyses in section 4. Our paper is concluded in section 5.

2. Model

In this section, we embed a technology network into an otherwise standard multi-sector quality-ladder model, featuring both intrasectoral and intersectoral knowledge spillovers.

2.1. Model Environment

The economy admits a unit measure of continuum identical households who choose the consumption in each period to maximize their lifetime utility, which takes the form as follows:

$$U = \sum_{t=0}^{\infty} \beta^t \log c_t, \tag{1}$$

where $\beta > 0$ is the time discount factor.

A representative household is endowed with one unit of labor, which is inelastically supplied to either the manufacturing market L_t^Y or innovation L_t^A at the wage rate w_t. The budget constraint at period t is:

$$P_t c_t + a_{t+1} \leq (1 + r_t) a_t + w_t, \quad \forall t = 0, 1, 2, \cdots \tag{2}$$

where P_t is the price of the consumption good, a_t is the asset of the household at period t, and r_t is the risk-free interest rate. The representative household maximizes its lifetime utility (1) subject to the budget constraint (2), leading to the standard consumption Euler equation:

$$\frac{P_{t+1}}{P_t} = \beta(1 + r_{t+1}) \frac{c_t}{c_{t+1}}. \tag{3}$$

The optimal choice ensures that the household is indifferent between consuming one unit of goods at period t and delaying consumption to period $t + 1$.

The final good Y_t is produced by combining sectoral goods from N sectors according to the following technology:

$$Y_t = \prod_{i=1}^{N} Y_{i,t}^{\alpha_i}, \tag{4}$$

where $Y_{i,t}$ is the intermediate input produced in sector i, and α_i is the relative importance of sector i for the production of the final good. $\sum_{i=1}^{N} \alpha_i = 1$. The final good producer maximizes its profit

$$\Pi_t = P_t Y_t - \sum_{i=1}^{N} P_{i,t} Y_{i,t}, \tag{5}$$

subject to production function (4), where $P_{i,t}$ is sector i's composite price. It yields:

$$P_{i,t} Y_{i,t} = \alpha_i P_t Y_t. \tag{6}$$

Equation (6) implies that the expenditure share of any sector is equal to its importance in the production of final good. The intermediate good $Y_{i,t}$ is a CES aggregate of different varieties produced by individual firms. Specifically,

$$Y_{i,t} = \left[\int_0^{H_{i,t}} z_{i,f,t}^{\frac{1}{\varepsilon}} \left(q_{i,f,t} \right)^{\frac{\varepsilon-1}{\varepsilon}} df \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{7}$$

where $\varepsilon > 1$ is the elasticity of substitution between varieties, $q_{i,f,t}$ is the quantity of the variety produced by firm f in sector i in period t and $z_{i,f,t}$ is the quality of this variety. Lastly, $H_{i,t}$ denotes the measure of varieties (firms) in sector i, which evolves over time.

The sectoral good producer aims to maximize her profit $\pi_{i,t}$ by choosing the amount of quantity $q_{i,f,t}$ demanded for each variety:

$$\pi_{i,t} = \max_{\{q_{i,f,t}\}} \left\{ P_{i,t} Y_{i,t} - \int_0^{H_{i,t}} p_{i,f,t} q_{i,f,t} df \right\}, \tag{8}$$

subject to the production function (7), where $p_{i,f,t}$ is the price of the variety produced by firm f in sector i in period t. Profit maximization leads to the inverse demand function for each variety:

$$q_{i,f,t} = \left(\frac{P_{i,t}}{p_{i,f,t}} \right)^{\varepsilon} z_{i,f,t} Y_{i,t}. \tag{9}$$

Intuitively, the quantity demanded for firm f's product is inversely related to its price $p_{i,f,t}$ while positively correlated with the quality of the product $z_{i,f,t}$.

The sectoral price index is given by:

$$P_{i,t} = \left(\int_0^{H_{i,t}} z_{i,f,t} p_{i,f,t}^{1-\varepsilon} df \right)^{\frac{1}{1-\varepsilon}}. \tag{10}$$

Individual firms have access to a symmetric production technology that produces one unit of a variety by hiring one unit of labor:

$$q_{i,f,t} = l_{i,f,t}. \tag{11}$$

Each firm maximizes its profit by choosing the price of the variety it produces

$$\pi_{i,f,t} = \max_{p_{i,f,t}} \{ p_{i,f,t} q_{i,f,t} - w_t l_{i,f,t} \} \tag{12}$$

subject to the production technology and the inverse demand function. The optimal price is a constant markup over the marginal cost of production, which is equal to the wage rate w_t. Without loss of generality, we normalize the wage rate w_t to be one. Consequently:

$$p_{i,f,t} = \frac{\varepsilon}{\varepsilon - 1}. \tag{13}$$

Substitution of (13) back into the profit function (12), taking into account the production technology (11) and the inverse demand function (9), delivers the maximized profit:

$$\pi_{i,f,t} = \frac{1}{\varepsilon}\frac{z_{i,f,t}}{z_{i,t}}\alpha_i P_t Y_t, \tag{14}$$

where $z_{i,t} = \int_0^{H_{i,t}} z_{i,f,t} df$ is the quality index for sector i in period t. The intuition for equation (14) is straightforward. The profit of firm f depends positively on the relative quality of this firm's product, $z_{i,f,t}/z_{i,t}$. The higher the relative quality of a firm's product within a sector, the higher the demand for its product and thus the profit for this firm. In addition, the importance of a sector for the final good production determines the share of total revenue that this sector captures. Therefore, a higher sectoral importance α_i would benefit more for all firms operating in this sector. Lastly, the elasticity of intrasectoral substitution ε is negatively related with a firm's profit, because a higher substitution elasticity implies a weaker monopoly power of individual firms, leading to lower profits.

2.2. Innovation, Entry and Exit

In this section, we specify how entrepreneurs conduct innovations and produce new patents. At the beginning of each period, there is a unit measure of potential entrepreneurs in each sector. Entrepreneurs can direct their innovations towards any sector by incurring a sector-specific labor cost of $C(\epsilon_{i,t})$, which is a function of the probability of successful innovation $\epsilon_{i,t}$. This cost can be interpreted as expenses induced by hiring workers to conduct innovation. The cost function increases with $\epsilon_{i,t}$ and is convex, i.e., $C^{'}(\epsilon_{i,t}) > 0$ and $C^{''}(\epsilon_{i,t}) > 0$. We further impose the restriction that $C(\epsilon_{i,t}) \to \infty$ when $\epsilon_{i,t} \to 1$. These conditions ensure the existence of an interior solution for our model.

When an entrepreneur succeeds in innovation, she produces a new patent and designs a product based on the patent. Without loss of generality, the value of the outside option for all entrepreneurs is assumed to be zero, which leads to the following free-entry condition for each sector:

$$\epsilon_{i,t} v_{i,f,t} - C(\epsilon_{i,t}) = 0, \forall i = 1, \cdots, N, \tag{15}$$

where $v_{i,f,t}$ is the value of a patent for firm f in sector i at period t, which will be discussed later. The free entry ensures that the expected net value of entry is equalized across sectors. In equilibrium, potential entrepreneurs are indifferent when considering which sector to enter.

Every period an incumbent firm faces an exogenous destructive shock with a probability of δ that forces the firm to leave the market. Therefore, the evolution of the measure of the firms in sector i depends on the inflow of entrant firms and the outflow of incumbent firms:

$$H_{i,t+1} = (1-\delta)H_{i,t} + \epsilon_{i,t}. \tag{16}$$

In equilibrium, the measure of the firms in each sector $H_{i,t}$ is time-invariant, which implies that the inflow of entrant firms ϵ_i equals the outflow of incumbent firms $\delta H_{i,t}$.

2.3. Evolution of Product Quality

The quality of a new product is determined by two components: the average product quality in the same sector and a composite term that captures knowledge spillovers from both its own sector and other sectors. Specifically, the quality of a new product takes the form as follows:

$$z_{i,f,t+1} = \bar{z}_{i,t} + \frac{1}{H_{i,t}} \sum_{j}^{N} \Omega_{i,j} z_{j,t}, \tag{17}$$

where $\bar{z}_{i,t} = z_{i,t}/H_{i,t}$ is average product quality in sector i, and $\Omega_{i,j} \geq 0$, $i \neq j$, captures the technological interdependence of sector i on j.[4] Specifically, $\Omega_{i,j}$ measures the strength of average knowledge spillovers from sector j to sector i, which is assumed to be exogenous. If $\Omega_{i,j} = 0$, then knowledge accumulations in sector j do not benefit innovation in sector i. Note that the model degenerates into a stan-

[4]The assumption that intersectoral knowledge spillovers play an important role in innovation is well documented by past studies (see, for example, the empirical analysis by Acemoglu et al. (2016)).

dard growth model without intersectoral knowledge spillovers when $\Omega_{i,j} = 0, \forall i \neq j$. The summation term captures the aggregate knowledge spillovers from the existing knowledge stock to sector i, which determines the size of the quality improvement for a new product. Lastly, the ratio $1/H_{i,t}$ is used to adjust the aggregate knowledge spillovers to measure the average spillovers.

The innovation network that determines the evolution of product quality is represented by the matrix containing $\{\Omega_{i,j}\}$. The innovation network governs the structure of technological interdependence in the economy and is the core of our analysis. Observe that individual sectors demonstrate both direct and indirect effects of knowledge spillovers. Direct knowledge spillovers from sector i to j exist if $\Omega_{i,j} > 0$, and indirect knowledge spillovers exist if there exist some sectors $(s_1, s_2, \cdots, s_n)$ such that $\Omega_{i,s_1}\Omega_{s_1,s_2}\cdots\Omega_{s_n,j} > 0$. Indirect knowledge spillovers generate a "ripple" effect that spreads knowledge beyond the neighboring sectors to the peripheral sectors. To ensure that all sectors converge to a balanced growth path, we assume, for the rest of this paper, that all sector pairs are either directly or indirectly connected. That is, the innovation network is strongly connected, the formal definition of which is as follows.

Definition 1. *An innovation network is a strongly connected network if* $\forall\ i \neq j$, $\exists$ *a sequence of sectors* $(s_1, s_2, \cdots, s_n)$ *such that* $\Omega_{i,s_1}\Omega_{s_1,s_2}\cdots\Omega_{s_n,j} > 0$.

Next, we aggregate individual firms' product quality to determine the evolution of the sectoral quality index. The quality index for sector i at time $t+1$ depends on the quality index of both incumbent firms and entrants. The dynamics of the quality index is shown as follows:

$$z_{i,t+1} = \int_0^{H_{i,t+1}} z_{i,f,t+1} df = (1-\delta) z_{i,t} + \int_0^{\epsilon_{i,t}} z_{i,f,t+1} df,\ \forall i = 1, \cdots, N. \tag{18}$$

Using (17) and the equilibrium condition $\epsilon_{i,t}/H_{i,t} = \delta$, the above equation can be rewritten as:

$$z_{i,t+1} = z_{i,t} + \delta \sum_{j=1}^{N} \Omega_{i,j} z_{j,t}, \ \forall i = 1, \cdots, N. \tag{19}$$

Equation (19) is intuitive. The evolution of a sector's quality index is closely related to this sector's position in the innovation network. A more central position for a sector implies that this sector receives stronger knowledge spillovers from other sectors in the innovation network. Indeed, a sector's position determines its relative product quality in the economy. In addition, the structure of the innovation network determines the growth rate of individual sectors and the economy's quality index. These findings are summarized in the following proposition. We delegate the proof of all propositions into the Appendix.

Proposition 1. *Define the growth rate of any sector i's product quality in period t as:*

$$g_{i,t} = \frac{z_{i,t} - z_{i,t-1}}{z_{i,t-1}}.$$

$g_{i,t}$ *asymptotically approaches the same limit* $\delta\lambda^*$*, where* λ^* *is the dominant eigenvalue of the matrix* Ω*. Define the relative product quality of sector i in period t as:*

$$M_{i,t} = \frac{z_{i,t}}{z_t},$$

where $z_t = \sum_i z_{i,t}$ *is the economy-wise quality index.* $M_{i,t}$ *approaches a constant* M_i *asymptotically, where* $\mathcal{M} = (M_1, \cdots, M_N)'$ *satisfies*

$$\Omega \mathcal{M} = \lambda^* \mathcal{M}. \tag{20}$$

This proposition sheds light on how the structure of the innovation network shapes the economy. To understand the first part of this proposition, note that (19) is a system of linear difference equations. Given that the dominant eigenvalue of Ω is nonzero, this system of equations admits a solution that expresses the quality index for any sector as a function of a linear combination of power functions with base terms equal to one plus the product of δ and the eigenvalues of Ω. In the limit, when t goes to infinity, the dominant eigenvalue dominates the process, therefore the growth rate converges to $\delta\lambda^*$. This result offers an elegant and simple way to characterize how the innovation network determines the speed of quality upgrading in equilibrium.

The second part of this proposition reveals a deep connection between the relative quality of a sector and its position in the downstream innovation network. First, notice that $\mathcal{M} = (M_1, \cdots \ M_N)'$ represents the *generalized right eigenvector centrality* in the innovation network.[5] The generalized eigenvector centrality measures the importance of a node in a network. In particular, a node gets higher scores if it is connected with other high score nodes. In our context, sectors benefit from knowledge spillovers from both their own sectors and others when conducting innovation. The eigenvector centrality of a sector reflects its position in the innovation network that determines the knowledge flows to the sector, which then determines the relative quality of products of the sector.

2.4. Equilibrium

In this section, we define the equilibrium for our economy and discuss the relationship between the patent value and network centrality.

Definition 2. *A balanced growth path equilibrium of the economy is a sequence of variables such that: (i) The representative household maximises the lifetime utility by choosing the consumption portfolio C_t, subject to the budget constraint; (ii) Given the prices of all sectoral goods $P_{i,t}$, the final product producer maximises his profit by choosing the demand for each sectoral good $Y_{i,t}$; (iii) Given the inverse demand function for each individual variety f in sector i and the wage rate w_t, the producer maximises his profit by choosing labor $l_{i,f,t}$, and the price of his product $p_{i,f,t}$ and the quantity of its product $q_{i,f,t}$; (iv) Entrepreneurs choose the innovation success probability $\epsilon_{i,t}$ to maximise the expected return of innovation and the free entry condition holds; (v) All markets clear.*

[5] The usual eigenvector centrality is associated with the undirected adjacency network; the notion of generalized eigenvector centrality here is adjusted for the weighted directed network.

Note that in equilibrium, the labor market clearing condition implies that:

$$\int_f l_{i,f,t} df = \int_f q_{i,f,t} df = L^Y. \tag{21}$$

Substituting the sectoral price index (10) into equation (9), and using the fact that $P_{i,t}Y_{i,t} = \alpha_i P_t Y_t$, gives:

$$q_{i,f,t} = \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{-1} \frac{z_{i,f,t}}{z_{i,t}} \alpha_i P_t Y_t. \tag{22}$$

The demand for the variety produced by firm f in sector i depends on the relative product quality in the sector. The combination of the demand function (22) and the labor market clearing condition (21), with some algebra, leads to

$$\alpha_i P_t Y_t = \frac{\varepsilon}{\varepsilon - 1} \frac{z_{i,t}}{z_t} L^Y. \tag{23}$$

The profit flow of the variety produced by firm f in sector i in period t is thus:

$$\pi_{i,f,t} = \frac{1}{(\varepsilon - 1)H_{i,t}} \sum_{j=1}^{N} \Omega_{i,j} \frac{z_{j,t-1}}{z_{t-1}} \frac{z_{t-1}}{z_t} L^Y. \tag{24}$$

Recall that along the balanced growth path, $M_j = \frac{z_{j,t}}{z_t}$ and $\frac{z_{t-1}}{z_t} = \frac{1}{1+g} = \frac{1}{1+\delta\lambda^*}$. From Proposition 1, $\sum_{j=1}^{N} \Omega_{i,j} M_j = \lambda^* M_i$, where λ^* is the dominant eigenvalue of the innovation network Ω. Consequently, we can rewrite the expected profit function as:

$$\pi_{i,f,t} = \frac{1}{\varepsilon - 1} \frac{M_i}{\epsilon_i} \frac{\delta\lambda^*}{1 + \delta\lambda^*} L^Y, \tag{25}$$

Equation (25) reveals that in equilibrium the profit flow of firm f in sector i depends positively on this sector's network centrality but negatively on the number of new patents. Intuitively, a higher centrality of a sector reflects a more central position of this sector in the innovation network, which provides an advantage for firms in this sector to conduct innovation as they benefit more spillovers from other sectors. On the other hand, the larger the number of new patents, the stronger the competition is, thus, the lower the profit. In equilibrium, the profit is constant over time. We drop the time and firm subscript when no confusion arises.

The previous discussions help to establish the value function of firm f with a patent in sector i:

$$v_i = \pi_i + \frac{1}{1+r}(1-\delta)v_i. \tag{26}$$

Equation (26) states that the value of a firm in sector i is equal to the profit this firm receives at the current period plus the expected future value if this firm remains in the market. Note that $1-\delta$ is the probability of firm survival. With simple algebra, we can derive:

$$v_i = \frac{1+r}{(\varepsilon-1)(r+\delta)}\frac{M_i}{\epsilon_i}\frac{\delta\lambda^*}{1+\delta\lambda^*}L^Y, \tag{27}$$

where $r = 1/\beta - 1$ is the equilibrium risk-free interest rate and L^Y denotes the equilibrium amount of labor used in manufacturing, which is to be determined later.

The value function derived in (27) implies a close connection between research expenses and the network centrality. To see this point, recall that the free entry condition (15) pins down the relation between the research cost and the value of new patents. Combining (27) with the free entry condition (15) delivers the following result:

$$C(\epsilon_i) = \frac{1+r}{(\varepsilon-1)(r+\delta)}\frac{\delta\lambda^*}{1+\delta\lambda^*}M_iL^Y \tag{28}$$

To close the model, we further assume that, for any potential entrant firm f, to obtain innovation success probability $\epsilon_{i,t}$ in sector i in period t, it requires to hire $l^A_{i,f,t}(\epsilon_{i,t}) = \frac{\epsilon_{i,t}}{1-\epsilon_{i,t}}$ units of labor, for all i and all t.

Since w_t is normalized to unity and the measure of potential firm entrants is also unity, the total cost of all innovation for sector i in period t is given by:

$$C(\epsilon_{i,t}) = \frac{\epsilon_{i,t}}{1-\epsilon_{i,t}},\ \ \epsilon_{i,t} \in [0,1], \forall i, \forall t. \tag{29}$$

Applying the above function to (28) gives a solution for ϵ_i in equilibrium:

$$\epsilon_i = \frac{\chi M_i}{1+\chi M_i}, \tag{30}$$

where $\chi = \frac{1+r}{(\varepsilon-1)(r+\delta)} \frac{\delta\lambda^*}{1+\delta\lambda^*} L^Y$. The measure of entrants in sector i, i.e. ϵ_i, is positively related to this sector's technology centrality. Intuitively, higher technology centrality implies higher profit of innovations, which induces more entrants. However, note that the marginal impact of technology centrality on innovation is diminishing due to the convexity of the cost function.

Integrating over $l^A_{i,f,t}(\epsilon_{i,t})$ gives the total labor demand for innovation workers:

$$L^A = \sum_i^N \chi M_i \epsilon_i = \sum_i^N \frac{\chi^2 M_i^2}{1+\chi M_i}. \tag{31}$$

Lastly, the total demand for labor is equal to the supply of labor in equilibrium:

$$L^A + L^Y = 1. \tag{32}$$

The above two equations, together with the definition of $\chi = \frac{1+r}{(\varepsilon-1)(r+\delta)} \frac{\delta\lambda^*}{1+\delta\lambda^*} L^Y$, determine the values of L^Y, L^A and χ. Substituting the value of L^Y back into(28), we obtain the following proposition:

Proposition 2. *The cost of innovation is higher for sectors with higher innovation network centrality, holding everything else constant.*

Now we explore the relationship between the value of patents and the corresponding sectoral centrality. Combining (27) and (30) delivers the following result:

$$v_i = 1 + \chi M_i, \tag{33}$$

which is formally stated in the following key proposition.

Proposition 3. *The value of a patent depends positively on the technology centrality of the sector that this patent belongs to.*

This proposition relates the position of a sector in the innovation network to the value of patents invented in this sector. It suggests that a sector's technology centrality is a sufficient statistic that summarises the impact of knowledge spillovers on the value of innovations. This sufficient statistic nests the standard intrasectoral knowledge spillover effect as a special case and goes beyond that by incorporating intersectoral knowledge spillovers. Proposition 3 highlights that innovations in sectors with higher centrality are more valuable than their counterparts in less central sectors.

Observe that there are two channels through which technology centrality affects innovation value. The first channel is the knowledge spillover effect, which contributes positively to value of a patent by enhancing the quality of the patent. This effect captures the benefits that new innovations receive from previous innovations through the innovation network. The second channel is the competition effect, which tends to reduce the patent value because a higher sectoral centrality results in more entrants, as suggested by (30), and thus generates more competition and smaller profit. This effect is clearly shown by (27), where the number of new entrants ϵ_i appears in the denominator of the patent value function. Overall, the positive knowledge spillover effect dominates the negative competition effect, making the net effect positive.

3. Data

This section describes the data and the methods that we use to construct the technology centrality and value of patents in our empirical analyses.

3.1. Patent Citation

The backbone for our analyses is the patent data (PATSTAT Global) from the European Patent Office,[6] which covers more than 100 million patent documents from leading industrialised and developing countries between 1927 and 2022. This data set provides detailed information on patent assignees, citations, the patent applied and granted dates, and a cooperative patent classification (CPC) number that differentiates individual patents based on their technological fields.[7] Following Acemoglu et al. (2016), we construct a proxy of intersectoral knowledge spillovers using the patent citation data:

$$\omega_{ij,t} \equiv \frac{Citations_{j\to i}^{t-3\to t-1}}{\sum_{k=1}^{N} Citations_{k\to i}^{t-3\to t-1}}, \quad i,j = 1,\cdots,N. \tag{34}$$

The notation $j \to i$ designates a patent citation from technology i to j, which in turn means knowledge flowing from technology j to i, and N is the number of technological sectors in the economy. $\omega_{ij,t}$ is, therefore, a normalized measure of knowledge spillovers from j to i in period t, the time average of which is an empirical counterpart of $\Omega_{i,j}$ discussed in our model. We construct our measure using citation data generated from patents granted over a 3-year window to alleviate the potential measurement error arising from annual observations. We also consider longer time periods using 5-year data in our empirical analyses.

Next, we proceed to construct the technology centrality measure based on (20). Specifically, we use ω_{ij} to form a matrix that represents the innovation network. We then calculate the dominant eigenvalue and the corresponding dominant eigenvectors of the innovation matrix. The dominant eigenvector for sector i, denoted by M_i, is the empirical measurement of sectoral technology centrality in our model.

[6] The data we use is the PATSTAT Global 2022 Spring edition.

[7] The US Patent Classification (USPC) System was used by the United States Patent and Trademark Office to classify patents. However, since January 1, 2013, this system has been replaced by the Cooperative Patent Classification (CPC) system.(Qiu and Wan, 2015; Strumsky and Lobo, 2015).

We construct an innovation network based on the aforementioned method using patent citation data between 1960 and 2018, which is shown the following figure.

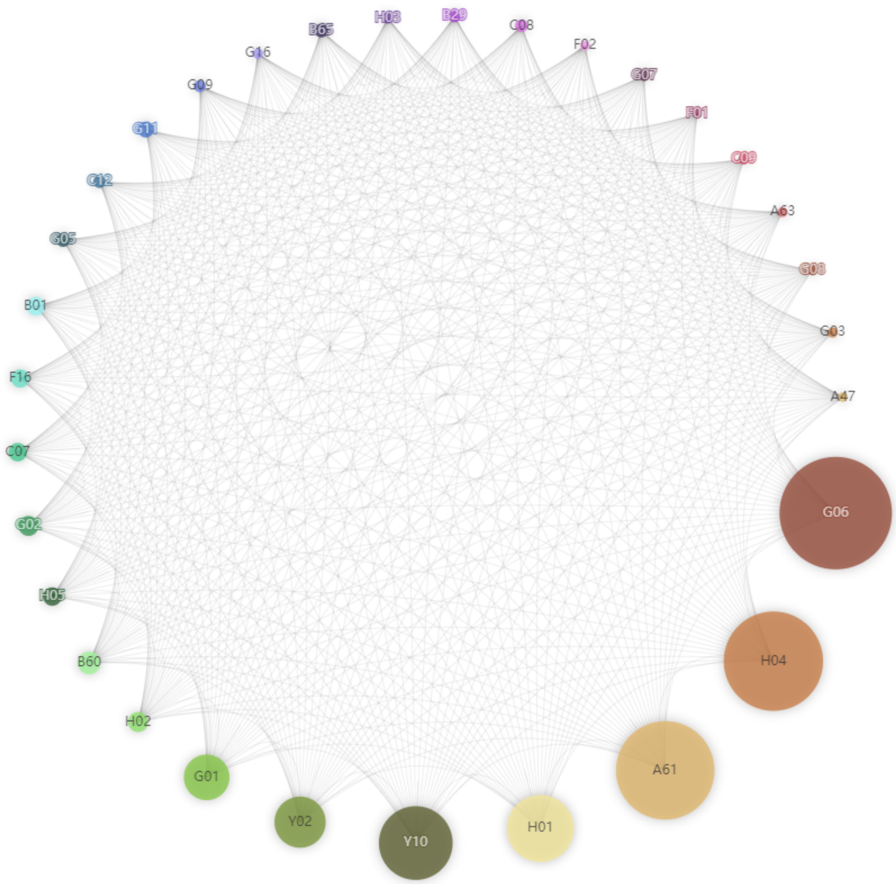

Figure 1: The Innovation Network (1960-2018)

Notes: Calculated using sectoral citations from 1960 to 2018. The size of each node represents the centrality of each technological class, which was calculated using Equation (20). Nodes with centrality lower than the mean are omitted. Sectors with the highest centrality are as follows: technologies for computing, calculating, and counting (G06), electric communication techniques (H04), medical or veterinary science, hygiene (A61), electric elements (H01), former USPC Technical subjects (Y10).

Figure 1 visually presents the innovation network calculated using sectoral citations from 1960 to 2018. Each node in the network represents a technological sector with a specific CPC classification, and is visualized with a distinct color. A larger size of a node means that the corresponding sector has a higher eigenvalue centrality. The directed edges in the network represent the flows of knowledge between these sectors. The direct knowledge spillover from sector j to sector i is from $\omega_{i,j}$ as calculated in Equation (34).

As we can see, Figure 1 showcases a substantial asymmetric network structure, where a few sectors occupy central positions in the network, while most other sectors reside remotely. For example, Sectors G06, H04, and A61[8] are the top three sectors in terms of centrality, and knowledge spillover from Sector C30 (crystal growth for Chemistry and Metallurgy) to Sector H01 (electric elements) is the strongest[9].

The following table provides the information about the sample distribution of sectoral technology centrality.

[8]technologies for computing, calculating, and counting (G06), electric communication techniques (H04), medical or veterinary science, hygiene (A61)

[9]When accounting for self-spillover effects, Sector A61 (medical or veterinary science, hygiene) has the highest eigenvalue centrality.

Table 1: Descriptive Statistics of Sectoral Centrality

	Sectoral Centrality	
	M_i^3	M_i^5
Mean	0.008	0.008
Std. Dev	0.017	0.016
Percentiles		
p1	0	0
p5	0	0
p10	0	0
p25	0.001	0.001
p50	0.003	0.003
p75	0.008	0.008
p90	0.017	0.017
p95	0.029	0.03
p99	0.09	0.09

Notes: The table presents the distribution of sectoral centrality from 1960 to 2022. Sectoral centrality is calculated using citations data as in Equation (34) and Equation (20). M_i^3 is generated using a three-year window, while M_i^5 is generated using a five-year window. The sample comprises a total of 8,127 observations.

As shown in Table 1, there exists substantial heterogeneity of network centrality across sectors, which is useful for our empirical analyses as we rely on the variations of sectoral centrality to explore the impacts of technology centrality on patent values and R&D expenses.

3.2. Patent Value

We follow the method developed by Kogan et al. (2017) to estimate the economic value of patents.[10] The estimation is mainly based on an event study method using

[10]The KPSS data set offers patent values at the firm level, assuming that patent value follows a positive normal distribution. However, they do not provide patent value in other specifications. Therefore, to test different distributions in terms of patent values and their associated error terms, we follow Kogan et al. (2017) method and re-estimate the patent values.

the stock market responses to the announcement of a patent grant.[11] We briefly introduce the method here.

First, each firm's idiosyncratic return from a patent grant is calculated by subtracting the return on the market portfolio from the firm's return. Specifically, the idiosyncratic stock return R_k for a given firm around the time that its patent k is issued is given by:

$$R_k = \nu_k + \iota_k \tag{35}$$

where ν_k is the intrinsic economic value of patent k measured as a fraction of the firm's market capitalization, and ι_k is a random component of the firm's stock return unrelated to the patent.

The economic value of patent k is estimated as the product of the estimate of the stock return times the market capitalization Υ_k of the firm, adjusted by the number of patents issued to the firm on the same day:

$$PV_k = (1-\zeta)^{-1} \frac{1}{N_f} E\left[\nu_k \mid R_k\right] \Upsilon_k. \tag{36}$$

where ζ is the unconditional probability of a successful patent application. N_f is the number of patent grants to firm f at the same day. ν_k follows a left-truncated normal distribution, $\nu_k \sim \mathcal{N}^+\left(0, \sigma^2_{\nu kt}\right)$, and that the noise term is normally distributed, $\iota_k \sim \mathcal{N}\left(0, \sigma^2_{\iota kt}\right)$. Consequently, the expected value of ν_k conditional on R_k is:

$$E\left[\nu_k \mid R_k\right] = \delta R_k + \sqrt{\delta}\sigma_{\iota kt} \frac{\phi\left(-\sqrt{\kappa}\frac{R_k}{\sigma_{\iota kt}}\right)}{1-\Phi\left(-\sqrt{\kappa}\frac{R_k}{\sigma_{\iota kt}}\right)}, \tag{37}$$

where ϕ and Φ represent the standard normal probability distribution function and

[11] Before calculating patent value, we first match PATSTAT patent data with compustat firms using patent-permno matching file from https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data. The data was retrieved on September 1st, 2023.

cumulative distribution function respectively, and κ represents the signal-to-noise ratio:

$$\kappa = \frac{\sigma^2_{\nu kt}}{\sigma^2_{\nu kt} + \sigma^2_{\iota kt}}. \tag{38}$$

κ can be estimated by calculating the increase in the volatility of firm returns around the patent publication date using the following regression:

$$\log \left(R_{kt}\right)^2 = \gamma I_{kt} + \zeta Z_{kt} + \epsilon_{kt},$$

where R_{kt} refers to the three-day idiosyncratic return of firm k on day t. I_{kt} equals 1 if a patent is issued for a firm k at time t and 0 otherwise. Day of week and the firm-year fixed effect are included as controls Z_{kt}. The estimated signal-to-noise ratio is therefore $\widehat{\kappa} = 1 - e^{-\widehat{\gamma}}$. Lastly, $\sigma^2_{\iota kt}$ can be estimated using $\sigma^2_{\iota kt} = 3\sigma^2_{kt}\left(1 + 3d_{kt}\left(e^{\hat{\gamma}} - 1\right)\right)^{-1}$, where σ^2_{kt} is the conditional volatility of firm k at year t using the realized mean idiosyncratic squared returns, and d_{kt} is the fraction of trading days that are announcement days.

Following Kogan et al. (2017), we set γ and ζ to be 0.0143 and 0.55 respectively. With these estimates, we can calculate the market-based economic value of each patent $\widehat{PV_k}$. As robustness tests, we allow different distributional assumptions for ν_k and ι_k. We re-estimate the economic values of the patents when: (i) ν_k is modeled as an exponential distribution; and (ii) ν_k and ι_k follow a truncated Cauchy and a standard Cauchy distribution, respectively. The detailed construction processes can be found in Appendix B. The sample distributions of patent values under different assumptions of ν_k and ι_k are presented in Table 2. A common feature across different specifications is that patent value tends to be right-skewed, with more than half patents in our sample valued above 1 million dollars.

Table 2: Descriptive Statistics of Patent Value

	Truncated Normal		Exponential		Cauchy	
	$E[\nu_k\|R_k]$ (%)	PV_k (USDm)	$E[\nu_k\|R_k]$ (%)	PV_k (USDm)	$E[\nu_k\|R_k]$ (%)	PV_k (USDm)
Mean	0.317	9.92	0.391	12.258	0.135	4.774
Std. Dev	0.252	27.851	0.343	34.599	0.096	13.979
Percentiles						
p1	0.094	0.008	0.112	0.01	0.04	0.003
p5	0.126	0.03	0.152	0.037	0.051	0.013
p10	0.147	0.097	0.177	0.118	0.06	0.044
p25	0.187	0.687	0.228	0.842	0.079	0.293
p50	0.255	3.038	0.314	3.733	0.109	1.359
p75	0.364	9.003	0.45	11.082	0.159	4.166
p90	0.532	22.357	0.664	27.585	0.234	10.719
p95	0.706	39.025	0.876	48.437	0.299	18.932
p99	1.252	108.093	1.552	134.431	0.483	54.704

Notes: The table presents the distribution of following variables in our sample. The first variable is the expected patent value $E[\nu_k|R_k]$, which is based on Equation (37). The second variable is the filtered dollar value of patents, PV_k , which is calculated using Equation (36). The patent value is deflated to 1982 (million) dollars using the Consumer Price Index (the symbol CPIAUCNS on FRED). In addition to the baseline case, we present results using two alternative distributional assumptions described in Section 3.2. The sample in our study comprises $3,488,638$ patents from 1927 to 2022.

3.3. Firm Controls

We collect information on firms' fundamentals from CRSP/Compustat merged database for the period between 1968 and 2022. We then merge our patent data with the CRSP/Compustat database. We restrict the sample to firm-year observations with nonmissing SIC classification codes and omit financial firms (SIC ocdes 6000 to 6799) and utilities firms (SIC codes 4900 to 4949). The processing procedure leaves us with a sample of 17961 firms.

The key variables included in our empirical analyses are firms' R&D expenses, leverage ratio (defined as total debt over total asset), net operating cash flow, stock return, total assets, number of employees and the firm's log idiosyncratic volatility.[12] The summary statistics of the firm variables are reported in Table 3.

Table 3: Summary statistics

Variable	N	Mean	Median	SD	Min	Max
R&D	83175	16.179	16.191	2.255	6.908	25.017
Leverage	155757	0.227	0.185	0.245	0	17.781
Cash	106181	17.547	17.586	2.443	6.908	25.368
Return	141755	-0.02	0.02	0.639	-7.121	6.072
Asset	156245	19.362	19.228	2.362	6.908	27.589
Employment	150334	6.923	6.93	2.304	0	14.648
Volatility	1828721	-4.157	-4.194	0.469	-6.258	-1.540
Market Capitalization	1878148	15.231	15.223	2.713	5.774	21.677

Notes: The table presents descriptive statistics for the firm-level variables used in our empirical analyses. Leverage is measured by the debt to asset ratio (dt/at). R&D (xrd), Cash (oancf), Asset (at), and Employment (emp) are at logarithm scale. Stock return is calculated using the logarithm of price change (prcc_f) plus dividend per share (dvc/csho). Volatility is firm's mean realized idiosyncratic volatility. Market capitalization (DlyPrevCap) and Volatility are at daily frequency and measured at logarithm scale.

4. Empirical Analysis

In this section, we formulate our empirical analyses based on the predictions of our model. We first test the relation between firms' technology centrality and the corresponding R&D expenses. Our model implies a positive correlation between firms' technology centrality and their R&D expenses, which constitutes the first hypothesis in our analysis. We then examine the key prediction of our model, which relates each sector's technology centrality to the value of innovations.

[12]We lag 1 year for all firm-level controls for the empirical analysis.

4.1. R&D and Firm Centrality

Our first empirical analysis involves examining the relationship between firms' R&D expenses and their technology centrality. We construct a firm-specific measure of technology centrality that reflects the technology centrality of each firm's patent portfolio as follows:

$$FirmCentrality_{f,t} = \sum_{i \in \Omega_{f,t}} \frac{N_{i,f,t}}{N_{f,t}} M_i \tag{39}$$

where $\Omega_{f,t}$ is the set of technology sectors firm f innovates in, M_i is the sectoral centrality for sector i constructed previously, and $N_{i,f,t}$ and $N_{f,t}$ are the number of patents invented by firm f in sector i at year t and the total number of patents firm f invented at year t respectively. This firm-specific technology centrality is essentially a weighted average of sectoral technology centrality, with weights equal to the shares of patents granted to a firm in each sector over the total number of patents the firm invented. We then run the following regression:

$$\boldsymbol{R\&D_{f,t} = a_1\ FirmCentrality_{f,t} + \mathrm{a}\ Controls_{f,t} + \varepsilon_{f,t},} \tag{40}$$

The coefficient of interest is a_1, which is expected to be positive if a firm's technology centrality is positively related with their R&D expenses. We include a vector of controls that are potentially related to the R&D expenditure. Specifically, we include: the firm's leverage level and net operating cash flow, which account for firms' external and internal cost of financing respectively; the stock market return, since positive stock returns may signal growth potential for firms (Lach and Schankerman, 1989); total assets and the number of employees, which capture potential firm size effect on R&D expenses. We also control for the industry-year fixed effects and firm fixed effects to rule out potential impacts of product market dynamics and firm heterogeneity.

Table 4: R&D and Firm's Technology Centrality

	(1)	(2)	(3)	(4)	(5)
FirmCentrality	0.620***	0.279***	0.119***	0.024***	0.017***
	(39.509)	(26.696)	(13.051)	(4.276)	(3.101)
Leverage		-1.165***	-0.811***	-0.279***	-0.287***
		(-11.092)	(-9.802)	(-5.680)	(-5.702)
Cash		0.076***	0.072***	0.040***	0.039***
		(4.986)	(6.637)	(6.489)	(6.815)
Return		0.035***	0.048***	0.021***	0.013**
		(2.907)	(4.469)	(3.403)	(1.986)
Asset		0.751***	0.762***	0.398***	0.383***
		(24.439)	(26.783)	(15.261)	(14.675)
Employment		-0.129***	0.010	0.380***	0.377***
		(-5.014)	(0.351)	(13.230)	(11.917)
Firm FE	No	No	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
Industry FE	No	No	Yes	Yes	No
Industry × Year FE	No	No	No	No	Yes
Observations	31172	20575	20551	19898	17729
R^2	0.325	0.804	0.889	0.976	0.983

Notes: The table reports estimation results from Equation (40). The dependent variable is the logarithm of R&D expense (Compustat: XRD) for firm f at year t. The explanatory variable is calculated using 3-year window as in Equation (39) at logarithm scale. 5-year window centrality result can be see in Table A1. Controls includes firm's leverage ratio, net operating cash flow, stock market return, total assets and the number of employees. Leverage is measured by the debt to asset ratio. All controls are measured at logarithm scale (except Leverage ratio) and lagged 1 year for the empirical analysis. Depending on the specification we also include: firm fixed effects, year fixed effect, industry fixed effect, and industry-year fixed effects to rule out potential impacts of product market dynamics and firm heterogeneity. We report t-statistics in parentheses. Our standard errors are robust and clustered at year level. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are winsorized at the 1% level using annual breakpoints.

Table 4 reports the estimation results. In column (1), we run a simple OLS regression including the firm's technology centrality as the only independent variable. There is a strong positive correlation between individual firms' technology centrality and their R&D expenses. A 1% increase of a firm's technology centrality leads to a 0.62% increase of the firm's R&D expenses. Additional firm-level controls are added to our regression in column (2). We further control for the industry and year fixed effects in column (3) and the firm fixed effects in column (4). In the last column, we control for the industry-year fixed effects along with the firm fixed effects. With the inclusion of controls, the coefficient for the firm's technology centrality remains positive and statistically significant at the 1% level.

A potential concern of our empirical analysis is that firms' R&D expenses tend to fluctuate substantially due to either aggregate or individual shocks. Therefore, using annual data on R&D expenses can exaggerate potential measurement errors of the dependent variable. To alleviate this concern, we follow Chan et al. (2001) to construct the stock of R&D using the follow equation:

$$R\&DS_{f,t} = R\&D_{f,t}+0.8R\&D_{f,t-1}+0.6R\&D_{f,t-2}+0.4R\&D_{f,t-3}+0.2R\&D_{f,t-4}. \quad (41)$$

Essentially, the assumption here is that the productivity of each dollar of R&D spending declines linearly by 20 percent a year.[13] We re-estimate our models using the newly constructed dependent variable and present the estimation results in Table 5.

A comparison between Table 4 and Table 5 reveals that our estimation results are consistent. There is a stable positive relationship between firms' technology centrality and the R&D stock. The estimates for the firm's centrality are, in general, larger in the current regressions. For instance, for the model specification with all controls shown in column (5), the estimate for firms' technology centrality is 0.028, which is about 50% larger than the baseline result, while maintaining the same level of significance.

[13]Note that the baseline estimation shown previously corresponds to an extreme scenario where the productivity of R&D expenses declines by 100 percent.

Table 5: R&D Stock and Firm's Technology Centrality

	(1)	(2)	(3)	(4)	(5)
FirmCentrality	0.619***	0.276***	0.131***	0.041***	0.028***
	(38.216)	(25.667)	(14.346)	(7.303)	(5.139)
Leverage		-0.966***	-0.654***	-0.168***	-0.178***
		(-9.076)	(-7.798)	(-3.480)	(-3.639)
Cash		0.051***	0.049***	0.019***	0.020***
		(3.264)	(4.530)	(3.430)	(3.945)
Return		0.005	0.021**	-0.007	-0.019***
		(0.432)	(2.146)	(-1.253)	(-3.354)
Asset		0.781***	0.757***	0.381***	0.353***
		(25.081)	(26.293)	(14.543)	(13.283)
Employment		-0.118***	0.036	0.418***	0.427***
		(-4.570)	(1.317)	(15.056)	(14.042)
Firm FE	No	No	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
Industry FE	No	No	Yes	Yes	No
Industry × Year FE	No	No	No	No	Yes
Observations	25702	18805	18785	18252	16128
R^2	0.352	0.828	0.906	0.984	0.989

Notes: The table reports estimation results from Equation (40). The dependent variable is the logarithm of R&D stock calculated using Equation (41). The explanatory variable is calculated using 3-year window as in Equation (39) at logarithm scale. 5-year window centrality result can be see in Table A2. Controls includes firm's leverage ratio, net operating cash flow, stock market return, total assets and the number of employees. Leverage is measured by the debt to asset ratio. All controls are measured at logarithm scale (except Leverage ratio) and lagged 1 year for the empirical analysis. Depending on the specification we also include: firm fixed effects, year fixed effect, industry fixed effect, and industry-year fixed effects to rule out potential impacts of product market dynamics and firm heterogeneity. We report t-statistics in parentheses. Our standard errors are robust and clustered at year level. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are winsorized at the 1% level using annual breakpoints.

4.2. Patent Value and Sectoral Centrality

In this section, we investigate the relationship between the value of patents and sectoral centrality. In particular, we estimate the following model:

$$\boldsymbol{PV_{k,f,i,t}} = \boldsymbol{b_1 M_{i,t}} + \mathrm{b}\,\boldsymbol{Controls_{k,f,i,t}} + \boldsymbol{\varepsilon_{k,f,i,t}}, \tag{42}$$

where $PV_{k,f,i,t}$ is the estimated economic value of patent k invented by firm f in technology sector i at time t, and $M_{i,t}$ represents sector i's technology centrality at time t, which is constructed previously. The left-truncated normal distribution is assumed to estimate the economic value of patents for our baseline analysis, and exponential and cauchy distributions are used for robustness tests. We include a vector of patent-, firm- and sector-level controls. As shown by our model, the competition effects generated by rival patents in a sector negatively impact the value of patents in the same sector. We therefore include the number of patents granted to the sector that patent k belongs to on the same day when patent k was granted to control for the competition effects.[14]

Another factor included in our regression is the number of citations a patent receives. As shown by Kogan et al. (2017), patent citations are a good proxy for the quality of a patent, which is highly correlated with the economic value of the patent. Including patent citations in the regression rules out the possibility that our results are driven by the scientific value of patents instead of their positions in the innovation network.

Lastly, we include a set of firm-level controls. Specifically, we include the firm's log market capitalization measured on the day prior to the patent grant to control for potential effects of different firm size. Moreover, we include the firm's log idiosyncratic volatility because it mechanically affects the construction of the economic value of patents.

[14]We also try an alternative measure that uses the number of patents granted one year before t in our regressions, and our results are qualitatively similar.

In addition to the aforementioned controls, we experiment with different combinations of fixed effects to rule out omitted variable bias in our empirical analyses. Table 6 reports our estimation results.

Table 6: Patent Value Regression

	(1)	(2)	(3)	(4)	(5)
Sectoral Centrality	0.082***	0.380***	0.546***	0.110***	0.094***
	(3.777)	(7.725)	(14.496)	(17.835)	(23.136)
Observations	1708556	1708556	1708556	1707170	1689416
R^2	0.002	0.010	0.625	0.932	0.962
Controls					
Sectoral Competition	—	Y	Y	Y	Y
Patent Citations	—	—	Y	Y	Y
Volatility	—	—	Y	Y	—
Firm Size	—	—	Y	Y	Y
Firm FE	—	—	—	Y	—
Year FE	—	—	—	Y	—
Firm × Year FE	—	—	—	—	Y

Notes: The table illustrates the patent value regression. The dependant variable is $PV_{k,f,i,t}$, which is calculated using Equation (36) and then deflated to 1982 (million) dollars using the Consumer Price Index (the symbol CPIAUCNS on FRED). The main explanatory variable is Sectoral Centrality ($M_{i,t}$). We present results for 3-year window centrality in this table. 5-year window centrality result can be see in Table A3. Depending on the specification we also include: Sectoral Competition, measured as the new patents granted at the same day for the same technological class. Patent Citations, measured as $\log(1 + C)$, where C is the number of forward citations; firm's idiosyncratic volatility, measured as realized mean idiosyncratic squared returns; firm size, measured as market capitalization on the day prior to the patent issue date; firm fixed effects; year fixed effects; Column (4) use firm and year fixed effect separately, and Column (5) use Firm × Year fixed effect. We report t-statistics in parentheses. Our standard errors are robust and clustered at the the patent grant year. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are at logarithm scale and are winsorized at the 1% level using annual breakpoints.

Table 6 column (1) presents the results of an OLS regression with sectoral centrality as the only independent variable in the regression. Our results reveals a positive and significant relationship between sectoral centrality and the value of innovations. We then control for the sectoral competition in our regression in column (2). It is interesting to see that as sectoral competition is added to the regression, the estimate for sectoral centrality increases substantially. This is consistent with our model since the sectoral competition negatively correlates with the value of patents while positively relates to sectoral centrality. In the next column, we further control for patent citations, the firm's volatility and firm size. With these additional controls, our estimate for sectoral centrality becomes larger and more precise. In column (4), we include firm and year fixed effects to avoid any time-invariant firm characteristics and aggregate time shocks to bias our estimates.

Our analysis so far cannot exhaust all possible time-variant firm factors that can potentially correlate with sectoral centrality. To address this issue, we interact the firm fixed effects with the year fixed effects in our regression and present the results in the last column of Table 6. This specification allows us to utilize the cross-sectoral variation of patent values within firms on the same year to explore the impact of sectoral centrality, which is ideal for our analyses. Our previous findings remain valid in this setup. A 1% increase of sectoral centrality raises the average value of innovations by 0.1% approximately. This estimate is statistically significant at the 1% level.

4.3. Robustness Tests

A key assumption for the construction of the economic value of patents is that the intrinsic economic value of patents follows a left-truncated normal distribution. To access the robustness of our results against this assumption, we use alternative distributional assumptions of the intrinsic value of patents. Specifically, we allow the unconditional intrinsic value of patents to follow an exponential distribution and a truncated Cauchy distribution respectively, and estimate the value of patents.[15] Using these two alternative measures of patent value, we repeat the regressions in Table 6.

[15] The detailed construction process can be found in Appendix B.

Table 7: Alternative Patent Value Regression

	(1)	(2)	(3)	(4)	(5)
Panel A: Exponential					
Sectoral Centrality	0.082***	0.380***	0.547***	0.111***	0.094***
	(3.774)	(7.714)	(14.465)	(17.716)	(23.064)
Observations	1707172	1707172	1707172	1705784	1688031
R^2	0.002	0.010	0.623	0.930	0.960
Panel B: Cauchy					
Sectoral Centrality	0.071***	0.386***	0.514***	0.109***	0.094***
	(3.276)	(7.840)	(13.789)	(16.518)	(23.711)
Observations	1751785	1751785	1702351	1700984	1733200
R^2	0.001	0.010	0.600	0.910	0.947
Controls					
Sectoral Competition	—	Y	Y	Y	Y
Patent Citations	—	—	Y	Y	Y
Volatility	—	—	Y	Y	—
Firm Size	—	—	Y	Y	Y
Firm FE	—	—	—	Y	—
Year FE	—	—	—	Y	—
Firm × Year FE	—	—	—	—	Y

Notes: The table illustrates the alternative patent value regression. The main explanatory variable is Sectoral Centrality ($M_{i,t}$). We present results for 3-year window centrality in this table. 5-year window centrality result can be see in Table A4. Depending on the specification we also include: Sectoral Competition, measured as the new patents granted at the same day for the same technological class. Patent Citations, measured as $\log(1 + C)$, where C is the number of forward citations; firm's idiosyncratic volatility, measured as realized mean idiosyncratic squared returns; firm size, measured as market capitalization on the day prior to the patent issue date; firm fixed effects; year fixed effects; Column (4) use firm and year fixed effect separately, and Column (5) use Firm × Year fixed effect. We report t-statistics in parentheses. Our standard errors are robust and clustered at the the patent grant year. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are at logarithm scale and are winsorized at the 1% level using annual breakpoints.

The estimation results for the two alternative measures of patent values are shown in Table 7. Panel A displays the results when the exponential distribution is assumed while Panel B shows the results for the Cauchy distribution. Consistent patterns arise from a comparison between Table 6 and Table 7: the estimate for sectoral centrality is mostly precisely estimated when the firm-year fixed effects is controlled in the regression regardless which measure of dependent variable is used. The magnitude and significance of the estimates in Table 7 are in close proximity of that in Table 6, indicating a stable relation between sectoral centrality and the value of patents.

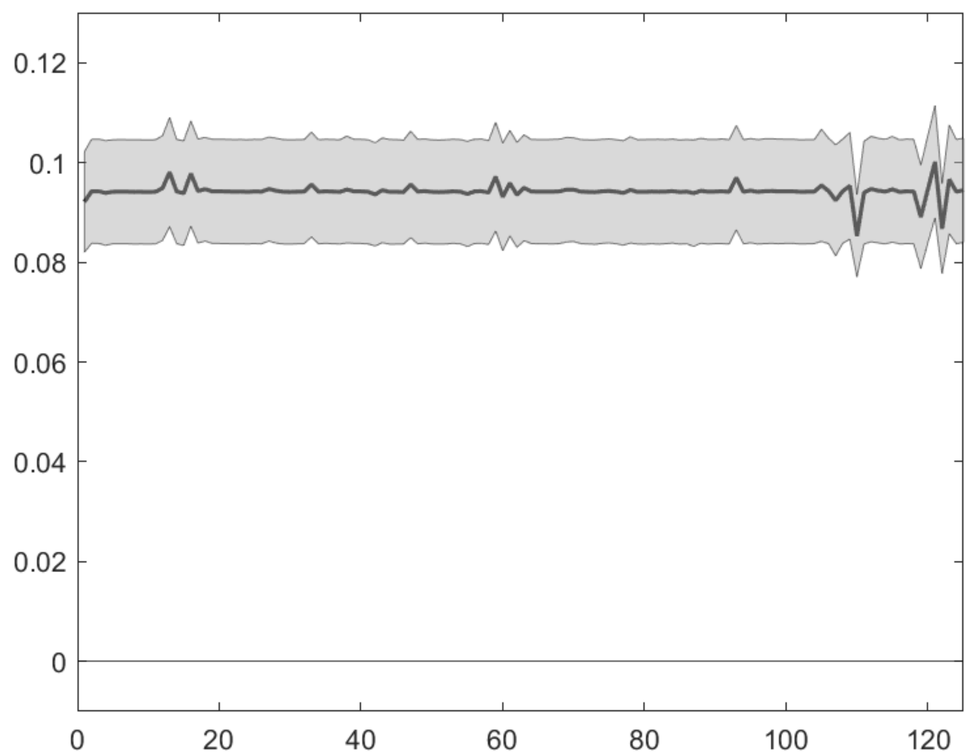

Figure 2: Sensitivity Test

Notes: This figure plots the sensitivity test for the patent value regression as in Column (5) of Table 6; Each data point represents the average estimate for the sectoral technological centrality when excluding one technology sector from the regression. Other coefficient estimates from regression are omitted. The 99% confidence interval is indicated by the upper and lower bounds.

Another concern of our empirical analyses is that the relation between the sectoral centrality and the value of innovations may be driven by individual technology sectors instead of a general network property shared by all sectors. To alleviate this concern, we conduct a sensitivity test by re-estimating the patent regression using the model specification in column (5) Table 6 multiple times, each time a technology sector is excluded from the regression.

Figure 2 pools together the point estimates with 99% confidence interval for all regressions ran in the sensitivity test. The middle solid line captures the coefficient estimate of the sectoral centrality for each regression, while the upper and lower bounds constitute the 99% confidence interval. As shown by Figure 2, the estimate for the sectoral centrality remains positive and statistically significant at the 1% level independent of which technology sector is excluded from the regression. More strikingly, the magnitude of estimates from different regressions are extremely close to each other, most of which center around 0.09, indicating a stable relationship between the sectoral centrality and the value of patents.

new section

5. Conclusion

Our paper offers both novel theoretical insights and new empirical evidence on the relationship between the structure of a technology network and the value of innovations. We investigate this relation through the lens of a quality-ladder innovation model with technological interdependence across sectors. Our model shows that the extent of quality improvement of new innovations in a sector is determined by the technology centrality of the corresponding sectors, which captures the position of the sector in the technology network. Innovations in sectors with greater technology centrality benefit more from knowledge spillovers and therefore demonstrate higher market value to their inventors, which also results in more R&D expenses.

We use a comprehensive patent citation database, complemented with the financial information from Compustat/CRSP to empirically confront the predictions of our model with data. The sectoral centrality is calculated by computing the eigenvectors of the empirically constructed technology matrix with the guidance of our model, and the economic values of patents are estimated using an event study method that relies on the stock market responses to corporate patenting activities. Our empirical analyses provide strong and robust support for the importance of technology centrality as predicted by our model. More specifically, a 1% increase in technology centrality of a sector is associated with an approximately 0.1% increase in the average economic value of patents in that sector.

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., and Kerr, W. (2018). Innovation, reallocation, and growth. *American Economic Review*, 108(11):3450–91.

Acemoglu, D., Akcigit, U., and Kerr, W. R. (2016). Innovation network. *Proceedings of the National Academy of Sciences*, 113(41):11483–11488.

Acemoglu, D. and Azar, P. D. (2020). Endogenous production networks. *Econometrica*, 88(1):33–82.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Aghion, P., Harris, C., and Vickers, J. (1997). Competition and growth with step-by-step innovation: An example. *European Economic Review*, 41(3-5):771–782.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

Akcigit, U. and Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy*, 126(4):1374–1443.

Austin, D. H. (1993). An event-study approach to measuring innovative output: The case of biotechnology. *The American Economic Review*, 83(2):253–258.

Ballester, C., Calvó-Armengol, A., and Zenou, Y. (2006). Who's who in networks. wanted: The key player. *Econometrica*, 74(5):1403–1417.

Baqaee, D. R. (2018). Cascading failures in production networks. *Econometrica*, 86(5):1819–1838.

Cai, J. and Li, N. (2019). Growth through inter-sectoral knowledge linkages. *The Review of Economic Studies*, 86(5):1827–1866.

Chan, L. K. C., Lakonishok, J., and Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance*, 56(6):2431–2456.

Chen, M. A., Wu, Q., and Yang, B. (2019). How valuable is fintech innovation? *The Review of Financial Studies*, 32(5):2062–2106.

Cohen, W. M. and Levinthal, D. A. (1989). Innovation and learning: the two faces of R&D. *The Economic Journal*, 99(397):569–596.

Elliott, M., Golub, B., and Leduc, M. V. (2022). Supply network formation and fragility. *American Economic Review*, 112(8):2701–2747.

Grossman, G. M. and Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, 58(1):43–61.

Hall, B. H. (1999). Innovation and market value. Working Paper 6984, National Bureau of Economic Research.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, pages 16–38.

Huang, J. and Xie, T. (2023). Technology centrality, bilateral knowledge spillovers and mergers and acquisitions. *Journal of Corporate Finance*, 79:102366.

Huang, J. and Zenou, Y. (2020). Key sectors in endogeneous growth. *CEPR Discussion Paper No. DP15281.*

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *The American Economic Review*, 76(5):984–1001.

Jaffe, A. B. (1989). Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy*, 18(2):87–97.

Jones, C. I. (1995). R&D-based models of economic growth. *Journal of Political Economy*, 103(4):759–784.

Kelly, B., Papanikolaou, D., Seru, A., and Taddy, M. (2021). Measuring technological innovation over the long run. *American Economic Review: Insights*, 3(3):303–320.

Klette, T. J. and Kortum, S. (2004). Innovating firms and aggregate innovation. *Journal of Political Economy*, 112(5):986 – 1018.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

König, M. D., Liu, X., and Zenou, Y. (2019). R&d networks: Theory, empirics, and policy implications. *The Review of Economics and Statistics*, 101(3):476–491.

Kortum, S. S. (1997). Research, patenting, and technological change. *Econometrica*, 65(6):1389–1419.

Lach, S. and Schankerman, M. (1989). Dynamics of R&D and investment in the scientific sector. *The Journal of Political Economy*, 97(4):880.

Levin, R. C., Cohen, W. M., and Mowery, D. C. (1985). R&D appropriability, opportunity, and market structure: new evidence on some schumpeterian hypotheses. *The American Economic Review*, 75(2):20–24.

Liu, E. and Ma, S. (2021). Innovation networks and R&D allocation. Working Paper 29607, National Bureau of Economic Research.

Nicholas, T. (2008). Does innovation cause stock market runups? evidence from the great crash. *American Economic Review*, 98(4):1370–96.

Pakes, A. (1985). On patents, R&D, and the stock market rate of return. *Journal of Political Economy*, 93(2):390–409.

Pakes, A. and Schankerman, M. (1984). An exploration into the determinants of research intensity. In *R&D, Patents, and Productivity*, pages 209–232. University of Chicago Press.

Qiu, J. and Wan, C. (2015). Technology spillovers and corporate cash holdings. *Journal of Financial Economics*, 115(3):558–573.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5):71 – 102.

Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patented inventions. *The American Economic Review*, 55(5):1097–1125.

Scherer, F. M. (1967). Market structure and the employment of scientists and engineers. *The American Economic Review*, 57(3):524–531.

Strumsky, D. and Lobo, J. (2015). Identifying the sources of technological novelty in the process of invention. *Research Policy*, 44(8):1445–1461.

Appendix A. Proofs

Proof of Proposition 1. Rewrite (19) in the matrix form:

$$Z_{t+1} = (\mathbf{I} + \delta\mathbf{\Omega})Z_t,$$

where $\mathbf{I}$ is an identity matrix, Z_t is the vector of sectoral quality index and $\mathbf{\Omega}$ is the matrix representing the innovation network. The above system admits the following solution:

$$Z_t = (\mathbf{I} + \delta\mathbf{\Omega})^t Z_0, \quad \text{given } Z_0.$$

Given that the dominant eigenvalue of the innovation network Ω is positive, we can decompose $(\mathbf{I} + \delta\mathbf{\Omega})^t$ as follows

$$(\mathbf{I} + \delta\mathbf{\Omega})^t = \mathbf{V}(\mathbf{I} + \delta\mathbf{T})^t\mathbf{V}^{-1},$$

where

$$\mathbf{T} = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_N \end{bmatrix}, \quad \mathbf{V} = (\mathbf{V}_1, \mathbf{V}_2, \cdots, \mathbf{V}_N)$$

where $\{\lambda_k\}_{k\in\mathcal{N}}$ are the eigenvalues of the matrix $\mathbf{\Omega}$, and $\{\mathbf{V}_k\}_{i\in\mathcal{N}}$ are the corresponding eigenvectors. According to the Perron-Frobenius theorem, there is a dominant eigenvalue λ^* such that $\lambda^* \geq \lambda_k$, $\forall k \in \mathcal{N}$. Therefore, we can express the quality index of sector k at time t as

$$z_{k,t} = \sum_{l=1}^{N} c_{kl}(1 + \delta\lambda_l)^t = (1 + \delta\lambda^*)^t \sum_{l=1}^{N} c_{kl}(\frac{1 + \delta\lambda_l}{1 + \delta\lambda^*})^t,$$

where c_{kl} is a function of elements from $\mathbf{V}$, $\mathbf{V}^{-1}$ and Z_0. Let $\lambda^* = \lambda_1$, as $t \to \infty$, $z_{k,t} = c_{k1}(1 + \delta\lambda^*)^t$. The growth rate of sector k is thus equal to $g_k^A = \delta\lambda^*$, $\forall k \in \mathcal{N}$. Since the quality index of all sectors grow at the same rate, so does the economy-wise quality index. This completes the first part of the proof.

To prove the second part of the proposition, we divide both sides of (19) by z_t and expand the system of equations to obtain:

$$\begin{bmatrix} (z_{1,t+1} - z_{1,t})/z_t \\ \vdots \\ (z_{N,t+1} - z_{N,t})/z_t \end{bmatrix} = \delta \begin{bmatrix} \Omega_{11} & \cdots & \Omega_{1N} \\ \vdots & \ddots & \vdots \\ \Omega_{N1} & \cdots & \Omega_{NN} \end{bmatrix} \begin{bmatrix} M_{1,t} \\ \vdots \\ M_{N,t} \end{bmatrix},$$

which can be manipulated as follows

$$\begin{bmatrix} \frac{z_{1,t+1} - z_{1,t}}{z_{1,t}} \frac{z_{1,t}}{z_t} \\ \vdots \\ \frac{z_{N,t+1} - z_{N,t}}{z_{N,t}} \frac{z_{N,t}}{z_t} \end{bmatrix} = \delta \begin{bmatrix} \Omega_{11} & \cdots & \Omega_{1N} \\ \vdots & \ddots & \vdots \\ \Omega_{N1} & \cdots & \Omega_{NN} \end{bmatrix} \begin{bmatrix} M_{1,t} \\ \vdots \\ M_{N,t} \end{bmatrix}.$$

In the equilibrium, $g^A = g_k^A \equiv \frac{z_{k,t+1} - z_{k,t}}{z_{k,t}}$, $\forall k$. Therefore, the above system of equations can be written as

$$\begin{bmatrix} g^A M_1 \\ \vdots \\ g^A M_N \end{bmatrix} = \delta \begin{bmatrix} \Omega_{11} & \cdots & \Omega_{1N} \\ \vdots & \ddots & \vdots \\ \Omega_{N1} & \cdots & \Omega_{NN} \end{bmatrix} \begin{bmatrix} M_1 \\ \vdots \\ M_N \end{bmatrix}.$$

This can be expressed in a compact form as

$$\lambda^* \mathcal{M} = \mathbf{\Omega} \mathcal{M}.$$

This completes the proof. □

Appendix B. Alternative Patent Values Measure

Exponential

We first utilized an exponential distribution to model ν_k. Similarly to the previous method, we posit that the firm' stock return on the patent grant date conforms to a certain set of parameters and is given by the equation:

$$R_k = \nu_k + \iota_k$$

We now assume that ν_k follows an exponential distribution with the parameter $1/\sigma_{\nu_k}$. We attribute the noise term to be normally distributed, $\iota_k \sim \mathcal{N}\left(0, \sigma_{\iota kt}^2\right)$ as before. Based on these assumptions, we can proceed to calculate the conditional expectation of $E\left[\nu_k \mid R_k\right]$, which is expressed as follows:

$$E[\nu_k|R_k] = R_k + \sigma_{\iota k}\left(\sqrt{\frac{2}{\pi}}\frac{\exp(-\tilde{R}_k^2/2)}{G^c(\tilde{R}_k/\sqrt{2})} - \frac{\sigma_{\iota_k}}{\sigma_{\nu_k}}\right),$$

where G^c is the complementary error function (also referred to as the "Q-function"), which represents the probability that a normally distributed random variable will exceed a certain threshold value.

$$\tilde{R}_k = \frac{\sigma_{\iota_k}}{\sigma_{\nu_k}} - \frac{R_k}{\sigma_{\iota_k}}.$$

As before, we assume that the proportion $\sigma_{\nu_k}^2/\sigma_{\iota_k}^2$ remains the same for all firms. Moreover, we rely on our pre-existing estimates that yield $\sigma_{\nu_k}^2/\sigma_{\iota_k}^2 = 0.0143$. Based on these result, we proceed to calculate PV_k and subsequently deflate it to CPI, just like we did earlier.

Cauchy

We formulate ν_k and ι_k using a truncated Cauchy and a standard Cauchy distribution, respectively. As before, firm's stock return takes the form of:

$$R_k = \nu_k + \iota_k$$

The distribution of ν_k has been updated to be the positive half of a Cauchy distribution with its center at zero and scale parameter γ_ν. Similarly, the distribution of ι_k is described by a Cauchy distribution with the same center and a scale parameter of γ_ι. Therefore, R_k on the announcement date also follows a Cauchy distribution with a scale of $\gamma_\nu + \gamma_\iota$. Assuming that both ι_k and ν_k follow a Cauchy distribution, we can determine the conditional patent value as follows:

$$E[\nu_k|R_k] = \frac{\gamma_\nu(\Theta \ln(c(R_k)) + \Xi \arctan(\frac{R_k}{\gamma_\iota}) - 2\Theta \ln(\gamma_\nu) + \Gamma)}{2\gamma_\iota\gamma_\nu R_k \ln(c(R_k)) + \Pi \arctan\left(\frac{R_k}{\gamma_\iota}\right) - 4\gamma_\iota\gamma_\nu R_k \ln(\gamma_\nu) + \Psi},$$

where $\Xi = 2R_k\left(c(R_k) + \gamma_\nu^2\right)$, $\Gamma = R_k\pi\left(R_k^2 + (\gamma_\iota - \gamma_\nu)^2\right)$, $\Pi = 2\gamma_\nu\left(\gamma_\nu^2 - \gamma_\iota^2 + R_k^2\right)$, $\Psi = \pi\left(\gamma_\nu + \gamma_\iota\right)\left(R_k^2 + (\gamma_\iota - \gamma_\nu)^2\right)$, $\Theta = \gamma_\iota\left(c(R_k) - \gamma_\nu^2\right)$, and $c(R_k) = R_k^2 + \gamma_\iota^2$. As previous literature has mentioned, the second moments of the Cauchy distribution do not exist. Therefore, we use alternative methods to estimate the distribution parameters. We estimate the scale parameter of the noise term (γ_ι) as half of the interquartile range of firm-year idiosyncratic returns. We estimate the noise-to-signal ratio $\tilde{\kappa} = \gamma_\nu/(\gamma_\nu + \gamma_\iota) = 0.0143$.[16] Table 2 presents the distribution of our constructed patent value.

[16] See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data for details.

Appendix C.

Table A1: R&D and Firm's Technology Centrality

	(1)	(2)	(3)	(4)	(5)
FirmCentrality	0.626***	0.279***	0.119***	0.024***	0.017***
	(39.863)	(26.583)	(12.969)	(4.198)	(3.099)
Leverage		-1.171***	-0.813***	-0.279***	-0.287***
		(-11.150)	(-9.816)	(-5.678)	(-5.698)
Cash		0.076***	0.072***	0.040***	0.039***
		(4.996)	(6.646)	(6.489)	(6.815)
Return		0.034***	0.048***	0.021***	0.013**
		(2.838)	(4.468)	(3.404)	(1.986)
Asset		0.750***	0.762***	0.398***	0.383***
		(24.378)	(26.778)	(15.263)	(14.673)
Employment		-0.129***	0.009	0.380***	0.377***
		(-5.018)	(0.341)	(13.236)	(11.918)
Firm FE	No	No	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
Industry FE	No	No	Yes	Yes	No
Industry $\times$ Year FE	No	No	No	No	Yes
Observations	31172	20575	20551	19898	17729
R^2	0.328	0.803	0.889	0.976	0.983

Notes: The table reports estimation results from Equation (40). The dependent variable is the logarithm of R&D expense (Compustat: XRD) for firm f at year t. The explanatory variable is calculated using 5-year window as in Equation (39) at logarithm scale. Controls includes firm's leverage ratio, net operating cash flow, stock market return, total assets and the number of employees. Leverage is measured by the debt to asset ratio. All controls are measured at logarithm scale (except Leverage ratio) and lagged 1 year for the empirical analysis. Depending on the specification we also include: firm fixed effects, year fixed effect, industry fixed effect, and industry-year fixed effects to rule out potential impacts of product market dynamics and firm heterogeneity. We report t-statistics in parentheses. Our standard errors are robust and clustered at year level. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are winsorized at the 1% level using annual breakpoints.

Table A2: R&D Stock and Firm's Technology Centrality

	(1)	(2)	(3)	(4)	(5)
FirmCentrality	0.625***	0.277***	0.131***	0.041***	0.028***
	(38.496)	(25.586)	(14.288)	(7.278)	(5.154)
Leverage		-0.972***	-0.655***	-0.168***	-0.178***
		(-9.121)	(-7.806)	(-3.477)	(-3.634)
Cash		0.051***	0.049***	0.019***	0.020***
		(3.273)	(4.539)	(3.436)	(3.946)
Return		0.004	0.021**	-0.007	-0.019***
		(0.371)	(2.147)	(-1.251)	(-3.353)
Asset		0.780***	0.757***	0.381***	0.353***
		(25.017)	(26.280)	(14.541)	(13.279)
Employment		-0.118***	0.036	0.418***	0.427***
		(-4.568)	(1.306)	(15.063)	(14.044)
Firm FE	No	No	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
Industry FE	No	No	Yes	Yes	No
Industry $\times$ Year FE	No	No	No	No	Yes
Observations	25702	18805	18785	18252	16128
R^2	0.355	0.827	0.906	0.984	0.989

Notes: The table reports estimation results from Equation (40). The dependent variable is the logarithm of R&D stock calculated using Equation (41). The explanatory variable is calculated using 5-year window as in Equation (39) at logarithm scale. Controls includes firm's leverage ratio, net operating cash flow, stock market return, total assets and the number of employees. Leverage is measured by the debt to asset ratio. All controls are measured at logarithm scale (except Leverage ratio) and lagged 1 year for the empirical analysis. Depending on the specification we also include: firm fixed effects, year fixed effect, industry fixed effect, and industry-year fixed effects to rule out potential impacts of product market dynamics and firm heterogeneity. We report t-statistics in parentheses. Our standard errors are robust and clustered at year level. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are winsorized at the 1% level using annual breakpoints.

Table A3: Patent Value Regression

	(1)	(2)	(3)	(4)	(5)
Sectoral Centrality	0.081***	0.376***	0.562***	0.114***	0.096***
	(3.660)	(7.738)	(15.285)	(18.252)	(22.493)
Observations	1708560	1708560	1708560	1707174	1689420
R^2	0.002	0.009	0.625	0.932	0.962
Controls					
Sectoral Competition	—	Y	Y	Y	Y
Patent Citations	—	—	Y	Y	Y
Volatility	—	—	Y	Y	—
Firm Size	—	—	Y	Y	Y
Firm FE	—	—	—	Y	—
Year FE	—	—	—	Y	—
Firm × Year FE	—	—	—	—	Y

Notes: The table illustrates the patent value regression. The dependant variable is ξ_k, which is calculated using Equation (36) and then deflated to 1982 (million) dollars using the Consumer Price Index (the symbol CPIAUCNS on FRED). The main explanatory variable is Sectoral Centrality ($M_{i,t}$). We present results for 5-year window centrality in this table. Depending on the specification we also include: Sectoral Competition, measured as the new patents granted at the same day for the same technological class. Patent Citations, measured as $\log(1 + C)$, where C is the number of forward citations; firm's idiosyncratic volatility, measured as realized mean idiosyncratic squared returns; firm size, measured as market capitalization on the day prior to the patent issue date; firm fixed effects; year fixed effects; Column (4) use firm and year fixed effect separately, and Column (5) use Firm × Year fixed effect. We report t-statistics in parentheses. Our standard errors are robust and clustered at the the patent grant year. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are at logarithm scale and are winsorized at the 1% level using annual breakpoints.

Table A4: Alternative Patent Value Regression

	(1)	(2)	(3)	(4)	(5)
Panel A: Exponential					
Sectoral Centrality	0.081***	0.377***	0.562***	0.115***	0.096***
	(3.656)	(7.726)	(15.250)	(18.142)	(22.420)
Observations	1707176	1707176	1707176	1705788	1688035
R^2	0.002	0.009	0.624	0.930	0.960
Panel B: Cauchy					
Sectoral Centrality	0.070***	0.382***	0.527***	0.112***	0.096***
	(3.151)	(7.822)	(14.481)	(16.950)	(22.997)
Observations	1751789	1751789	1702355	1700988	1733204
R^2	0.001	0.009	0.601	0.910	0.947
Controls					
Sectoral Competition	—	Y	Y	Y	Y
Patent Citations	—	—	Y	Y	Y
Volatility	—	—	Y	Y	—
Firm Size	—	—	Y	Y	Y
Firm FE	—	—	—	Y	—
Year FE	—	—	—	Y	—
Firm × Year FE	—	—	—	—	Y

Notes: The table illustrates the alternative patent value regression. The dependant variable is patent value assuming exponential distribution. The main explanatory variable is Sectoral Centrality ($M_{i,t}$). We present results for 5-year window centrality in this table. Depending on the specification we also include: Sectoral Competition, measured as the new patents granted at the same day for the same technological class. Patent Citations, measured as $\log(1+C)$, where C is the number of forward citations; firm's idiosyncratic volatility, measured as realized mean idiosyncratic squared returns; firm size, measured as market capitalization on the day prior to the patent issue date; firm fixed effects; year fixed effects; Column (4) use firm and year fixed effect separately, and Column (5) use Firm × Year fixed effect. We report t-statistics in parentheses. Our standard errors are robust and clustered at the the patent grant year. *, **, and *** stands for the significance levels of 10%, 5%, and 1%, respectively. All variables are at logarithm scale and are winsorized at the 1% level using annual breakpoints.