Corporate R&D Spillovers and Investment in the Innovation Network

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Abstract

In this paper, I build a measure of technological distance between firms using the citation-based innovation network, which incorporates knowledge spillovers from upstream technological fields to downstream technological fields. I then use this measure to estimate the impact of technology spillovers using panel data on U.S. firms. I find that spillovers from firms innovating in upstream fields are quantitatively as important as spillovers from firms innovating in same fields. Consistent with the idea that firms innovate more when there is more past upstream innovation to build on, firms' R&D investments respond positively to R&D investments of firms in upstream fields, but not to R&D investments of firms in downstream fields or in the same fields. Smaller firms on average operate in more upstream technological fields and generate more spillovers and higher social returns, which is contrary to the findings of previous research.

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1. Introduction

Knowledge spillover from corporate investment on research and development (R&D) is important for understanding innovation and technological change, but spillovers are hard to measure empirically. Moreover, new innovations often build on past achievements in other areas, as the descriptive phrase "standing on the shoulders of giants" suggests. Firms that innovate in more "upstream" and fundamental technological areas would create larger knowledge spillovers to other firms in the society than firms in "downstream" technological areas. Nevertheless, the knowledge spillovers across technology areas has been largely ignored in previous studies. This paper delivers a framework in which it is possible to measure how important technology spillovers from upstream to downstream technological fields are for firm outcomes including patenting, productivity, investment and market value, and study which firms create the largest knowledge spillovers.

We build on the recent work by Bloom, Schankerman, and Van Reenen (2013, BSV in short), which develops a general framework incorporating two kinds of spillovers: a positive technology spillover and a negative business stealing effect from product market rivals. They use a Jaffe metric and a more general Mahalanobis metric to measure the closeness between firms in technology space and product space based on technology distribution of firms patents and industry composition of firm sales. An important insight from the paper is that the distances in the technology space and product space is uncorrelated, which creates enough variation to identify the two spillover effects separately.

Both the Jaffe metric and Mahalanobis metric do not consider an important aspect of knowledge spillovers: innovation is a cumulative process and new progress builds on past achievements. Acemoglu, Akcigit and Kerr (2014, AAK in short) shows that the knowledge spillovers in the form of "standing on the shoulders of giants" is huge: about half of the citations in patents are from outside the technology class, and number of patents in upstream technology classes has strong predictive power of the future innovation in downstream technology classes.

In this paper we develop a new "network measure" to measure the technology spillovers between firms, and the distance between different technology classes is based on citation patterns in AAK. We show that when using the network measure to calculate R&D spillovers, the spillovers from firms that are technologically connected has a positive and significant impact on firm's *R&D* and *patenting*, while spillovers have no significant impact on R&D and smaller impact on patenting when using other measures. This confirms our hypothesis that knowledge spillovers from upstream areas have a significant impact on downstream innovations. However, the R&D spillovers from firms close in technology space has the largest impact on firm's *productivity* and *market value* when we use the Mahalanobis distance measure to calculate spillovers. One explanation is that the network measure measures the pool of knowledge generating "innovation" spillovers which leads to higher innovation output due to a larger knowledge stock to build on, and the Mahalanobis measure measures the pool of knowledge generating "production" spillovers which leads to higher productivity due to technology adoption.

To examine the robustness of our finding, we first separately measure the impacts of spillovers within and across technology fields and show that spillovers across technology fields have a significant impact on firm outcomes. Second, we use patent stock rather than R&D stock as an alternative measure of firms' knowledge stock. We also study the effects of R&D spillovers over time and show that effects on patenting, market value and productivity persist over a long period.

Finally, we use our measure to study which firms generate the largest spillovers. The results are completely the opposite to BSV: while they find small firms operate in technological niches, we find they are more likely to operate in more upstream technology fields. This result suggests that the social return to R&D may be a lot higher than private R&D for small and young firms, and justifies providing R&D subsidies to these firms. In general, since the network measure takes into account the fundamental and upstream research done by firms which provides basis for later on innovations, it would allow us to better characterize the knowledge spillovers that leads to new innovations, and compare private vs. social returns to R&D.

The paper is organized as follows. Section 2 describes the network measure of technological distance between firms. Section 3 outlines a simple model of innovation network and the main empirical specifications. Section 4 describes the data we use. Section 5 and Section 6 presents the empirical results and some specification tests. In Section 7 we use the measure to identify which firms generate and receive the largest spillovers, and we conclude in Section 8.

2. The Network Measure of Technological Proximity

The conceptual framework for technology spillovers was first introduced by Griliches in 1979. In his seminal work, technological spillovers arise through a common pool of technological knowledge. Firms make use of the pool of knowledge as an additional input in their production functions. The R&D of one firm both affects the firm's own productivity and indirectly affects the productivity of other firms through the pool of knowledge. Jaffe (1986) introduced a technological distance between firms in order to capture the likelihood that technological spillovers would arise between firms. Two firms are more likely to benefit from R&D of each other if they are technologically close. Specifically, the spillover from firm j to firm i is:

$$SPILLOVER_{ij}^{J} = TECH_{ij}^{J} n_j$$

$$TECH_{ij}^{J} = n_i F_i F_j' = \sum_{\tau} \sum_{\tau'} n_i F_{i\tau} F_{j\tau'}$$

where n_i is number of patents by firm i. The $1 \times Y$ vector $F_j = (F_{j1}, ..., F_{j\tau})$ is defined as in BSV, where $F_{j\tau} = \frac{n_{i\tau}}{n_i}$ is the share of patents in technology class τ of all firm i's patents. If we think of n_i as a proxy for the number of scientists in firm i, the measure of spillover is exactly the number of encounters between scientists from firm i and j [1].

[1] The measure of spillover we consider in this paper is the "exposure" measure in BSV, while the traditional Jaffe measure normalizes the uncentered covariance on the standard deviation of the share vectors F. Both measures lead to very similar results as shown in BSV.

The BSV also extends the Jaffe measure to Mahalanobis measure, which considers technological spillovers between closely related fields.

$$TECH_{ij}^{M} = n_i F_i \Omega F_j' = \sum_{\tau} \sum_{\tau'} n_i F_{i\tau} \omega_{\tau\tau'} F_{j\tau'}$$

where $\Omega = [\omega_{\tau\tau'}]$ denotes the $Y \times Y$ matrix that describes the probability of knowledge transfer when two scientists from fields τ and τ' meet, and is based on the extent of co-location of patenting across technology fields.

Both the Jaffe measure and Mahalanobis measure neglects the technology spillovers in the form of "standing on the shoulders of giants", meaning that firms innovating in more upstream and more fundamental technology fields creates larger knowledge spillovers to the rest of the firms in the economy. By considering spillovers from more upstream fields to more downstream fields, my methodology also captures asymmetries in spillovers, which are ruled out by construction in distance measures, like Jaffe and Mahalanobis. Allowing for asymmetric spillover effects is important since, as stated in Syverson (2011) page 349: "Firms are likely to attempt to emulate productivity leaders in their own and closely related industries". That is, spillovers are likely to originate in high productive firms and cascade down to less productive firms.

In particular, we develop a measure of spillover from firm j to firm i based on patent citations network:

$$TECH_{ij}^{N} = n_i F_i C F_j' = \sum_{\tau} \sum_{\tau'} n_i F_{i\tau} C_{\tau\tau'} F_{j\tau'} \tag{1}$$

The $Y \times Y$ matrix C represents the patent citation network in AAK. The element $C_{\tau\tau'}$ is the share of patents in class τ that cites from a patent in class τ', which is the average number of times a patent in technology class τ' is cited by patents in technology class τ within 10 years of being granted divided by number of patents in technology class τ:

$$C_{\tau\tau'} = \sum_{a=1}^{10} \frac{\text{Citations}_{\tau \to \tau', a}}{\text{Patent}_{\tau'} \text{Patent}_{\tau}}$$

The measure $TECH_{ij}^{N}$ has an intuitive interpretation: it is the average number of times each patent in firm j gets cited by patents from firm i given the technology class distribution of the two firms. In particular, $F_{j\tau'}$ is the probability of firm j patenting in a particular technology class τ', and $C_{\tau\tau'}$ is the average share of patents in class τ that cites from this patent given its class τ', and $n_i F_{i\tau}$ is the number of patents in class τ from firm i.

We can then compute the pool of technology spillover to firm i in year t:

$$SPILLTECH_{it}^{N} = \sum_{j \neq i} TECH_{ij} G_{jt}, \tag{2}$$

where G_{jt} is the stock of R&D. The number of patent citations from firm i to firm j thus approximates the knowledge spillovers from firm j's R&D to firm i. This network measure will be the baseline measure for technology spillovers in our research. Intuitively, let's say firm j invests 1 million in R&D and produces 100 patents, and these 100 patents are cited by 1 patent from firm i on average, then our measure says that the 1 million R&D investment of firm j generates a technology spillover of 1 patent to firm i.

We can also decompose within-class and cross-class spillovers by writing $C = C^D + C^H$, where C^D is a diagonal matrix, and C^H is a matrix with all diagonal elements equal to zero. Then the network measure can be written as: $TECH_{ij}^{N} = n_i F_i C^D F_j' + n_i F_i C^H F_j'$.

There are several caveats with our construction of the network measure of proximity between firms. First, patent citations may not reflect actual knowledge flows. Sometimes citations are added by patent examinees after the patent has been applied, and our measure would overestimate cross-technology field spillovers if citing other fields are more likely to be added afterwards. Second, the network measure does not deal with measurement errors in assigning technology fields. If patent office examiners erroneously allocate patents in closely related fields, the Mahalanobis measure corrects it by recognizing the fields as close to each other, but the network measure won't recognize them if there are no patent citations between those fields. Finally, this measure does not differentiate between long-term and short-term spillovers. In particular, the R&D stock G_t comprises mostly of recent R&D investments when we choose a 15% depreciation rate, but some spillovers may take effect after more than 5 years, especially if across technology fields, and our measure of $SPILLTECH_{it}$ may overweight the R&D investments in more recent years.

3. Empirical Strategy

3.1 A simple model of innovation network

Suppose firm i has a product market competitor firm m_i and a technology neighbor τ_i . Firm i's profit is given by $\pi(x_i, x_m, k_i)$, where x_i is output or quantity, x_m is the output of quantity chosen by the firm's competitor firm m_i, and k_i is knowledge stock (or innovation output). Since in the last stage of each period, each firm chooses price and quantities given each other's knowledge stock, we can write profit as $\Pi(k_i, k_m, k_\tau)$. We generalize the function to also include the innovation output of firm τ to incorporate knowledge spillovers to firm i's productivity without affecting firm i's innovation, for example in the case of firm i's technology and firm τ's technology being complements in production.

At each period t, firm i produces its innovation with its own R&D, and spillovers from the R&D of firms to which it is close in the technology space:

$$k_i^t = \phi(r_i^t, k_i^{t-1}, k_\tau^{t-1}) \tag{3}$$

The k_τ^{t-1} in this function reflects the pool of knowledge that the firm builds its innovation on. The knowledge production function $\phi(.)$ is non-decreasing and concave in each argument. Firm i solves the following maximization problem:

$$\max_{r_i^t} V_i^t = \tilde{\Pi}(\phi(r_i^t, k_i^{t-1}, k_\tau^{t-1}), k_m^{t-1}, k_\tau^{t-1}) - c(r_i^t) \tag{4}$$

The function $\tilde{\Pi}$ is the expectation of firm's profits given the knowledge stock of product market rivals and technology space neighbors at time $t-1$.

In this stylized model there are only three firms, but we can easily generalize to the case with many firms. Suppose T is a matrix representing the network of interactions of all the firms in the technology space, and S is a matrix representing the network of interactions in the product space (both matrix has all diagonal elements equal to zero), then we can write:

$$k_\tau^t = T_i \mathbf{k}^t = \sum_{j \neq i} T_{ij} k_j^t, \;\; k_m^t = S_i \mathbf{k}^t = \sum_{j \neq i} S_{ij} k_j^t$$

and

$$r_\tau^t = T_i' \mathbf{r}^t = \sum_{j \neq i} T_{ij}' r_j^t$$

T' represents the innovation network, which may be different from T. As we've discussed in Section 2.2, T can be approximated by the Mahalanobis measure, and T' can be approximated by the network measure.

The first order condition of the maximization problem in (4) is: $\tilde{\Pi}_1 \phi_1 = c'(r_0^t)$, and the solution is:

$$r_i^{t*} = R(k_i^{t-1}, k_\tau^{t-1}, k_m^{t-1}) \tag{5}$$

Plug this into (3) and we get:

$$k_i^t = \phi(R(k_i^{t-1}, k_\tau^{t-1}, k_m^{t-1}), k_i^{t-1}, k_\tau^{t-1}) \tag{6}$$

The first k_τ^{t-1} in the above equation reflects endogenous effect of the innovation of technologically close firms on firm i's R&D: it can arise from the non-linearity of the profit function, or from strategic complementarity (or substitutability)[2] between R&D of firms with similar technologies. The sign of this effect is ambiguous. The second k_τ^{t-1} reflects technology spillover, which has a positive impact on firm i's innovation output. The k_m^t in the equation is the strategic effect of innovation output of product rivals: it has a positive effect if firm i's innovation and its competitor's innovation is strategic complements, and vice versa.

To be able to estimate the model, we assume both $\phi(.)$ and $\Pi(.)$ are linear. As shown in some theoretical literature on networks, many conclusions in the linear case can be generalized

[2]Examples of strategic complements include patent races and complementarity between closely related technologies, and examples of strategic substitutability include decreasing returns from innovating in a field and substitutability between similar technologies.

to non-linear cases as well. In particular, suppose that the knowledge production function is:

$$k_i^t = \phi(r_i^t, k_i^{t-1}, k_\tau^{t-1}) = (1-\delta)k_i^{t-1} + \alpha r_i^t + \sigma_i k_\tau^{t-1} + \gamma r_i^t k_\tau^{t-1} + \epsilon_i^t \quad (7)$$

where δ is the depreciation of knowledge stock, α is the return to R&D, σ_i is the direct spillover from R&D of technology neighbors, and γ reflects the strategic complementarity or substitutability of R&D investments between firms that are close in technology space; $\gamma > 0$ if firms can innovate more productively when building on a larger pool of knowledge. The payoff function is:

$$\max_{r_i} V_i^t = \tilde{\Pi}(k_i^t, k_m^{t-1}, k_\tau^{t-1}) - c(r_i) = (\beta_i k_i^t + \mu k_i^t k_m^{t-1} + \eta k_m^{t-1} + \psi k_\tau^{t-1} + \xi_i^t r_i) - \frac{1}{2}\theta r_i^2 \quad (8)$$

where $\mu > 0$ in the case of strategic complements, and η is the direct effect of knowledge stock of product market rivals on firm's profits. ψ reflects that firms produce more efficiently when the knowledge stock of their technology neighbors is larger. θ is the R&D cost parameter and may be affected by R&D tax credits. Solving the FOC and the optimal R&D is:

$$r_i^t = \frac{\alpha}{\theta}\beta_i + \frac{1}{\theta}\beta_i \gamma k_\tau^{t-1} + \frac{1}{\theta}(\alpha + \gamma k_\tau^{t-1})\mu k_m^t + \frac{1}{\theta}\xi_i^t \quad (9)$$

For simplicity we assume $\mu \approx 0$, so there is no strategic effects of R&D by product market rivals. We shall verify this in the empirical section. Plug into (7) and we get:

$$\begin{aligned} k_i^t - (1-\delta)k_i^{t-1} &= \alpha r_i^t + \sigma_i k_\tau^{t-1} + \gamma r_i^t k_\tau^{t-1} + \epsilon_i^t \\ &= \frac{\theta}{\beta} r_i^{t^2} + \sigma_i k_\tau^{t-1} + \epsilon_i^t & (10) \\ &= \frac{\alpha^2}{\theta}\beta_i + (\frac{2\alpha}{\theta}\beta_i\gamma + \sigma_i)k_\tau^{t-1} + \frac{1}{\theta}\beta_i\gamma^2 k_\tau^{t-1^2} + \tilde{\epsilon}_i^t & (11) \end{aligned}$$

Finally, the profit is:

$$\pi_i^t = \theta r_i^{t^2} + \beta_i(1-\delta)k_i^{t-1} + (\sigma_i\beta_i + \psi)k_\tau^{t-1} + \eta k_m^{t-1} + \varepsilon_i^t \quad (12)$$

One difficulty of empirically estimating these equations is how to measure knowledge R&D r^t and stock k^t. In practice R&D may take several years to take effect, so instead of current-period R&D, a better approximation would be R&D stock, which is the sum of R&D in recent years. For k^t, BSV approximates knowledge stock using the stock of R&D which is the sum of R&D investments and depreciates over time. This may lead to measurement errors especially for k_m^t: for example, the product market competitor firm m may invest little in R&D but has huge innovation outputs due to spillovers from his technology neighbors, then using R&D stock would underestimate k_m^t. As an alternative I also used the stock of patents as the knowledge stock of a firm. Using patent stock can be problematic too: there are many innovations that are not patented and cannot be captured by patents.

3.2 Empirical specifications

The generic equation we are estimating is:

$$\ln Q_{it} = \beta_1 G_{it-1} + \beta_2 \ln \mathit{SPILLTECH}_{it-1} + \beta_3 \ln \mathit{SPILLSIC}_{it-1} + \beta_4 X_{it} + u_{it} \tag{13}$$

where G_t is the stock of R&D, and is a proxy for the stock of knowledge k_t. We also use firms' patent stock to proxy for knowledge stock in robustness checks. The spillovers from technology neighbors *SPILLTECH* is defined in equation (2), and spillovers from product rivals is defined similarly using the Jaffe measure:

$$\mathit{SPILLSIC}_{it} = \sum_{j \neq i} \mathit{SIC}_{ij} G_{jt} = \sum_{j \neq i} n_i S_i S_j' G_{jt} \tag{14}$$

X_{it} is a vector of controls. To deal with unobserved heterogeneity, we include firm fixed effects (η_i) and year fixed effects (τ_t) in all regressions except patent equations, and allow the error term to be heteroskedastic and serially correlated.

The R&D on the right hand side may be endogenous due to transitory shocks. To address this concern, we follow BSV and use tax-induced changes to the user cost of R&D capital as instrument. The user cost of R&D differs across firms for two reasons: first, different states have different levels of R&D tax credits and corporation tax, which will differentially affect firms depending on their cross-state distribution of R&D activity; second, it also has a firm-specific component, in part because the definition of what qualifies as allowable R&D for tax purposes depends on a firm-specific "base". We use these tax policy instruments to predict R&D, and then use these predicted values to calculate predicted spillovers according to equations (2) and (14). The spillover terms are being instrumented by the values of other firms' tax prices, weighted by their distance in technology and product market space.[3]

First, we consider the R&D equation where the left hand side variable is R&D intensity:

$$\ln\left(\frac{R}{Y}\right)_{it} = \alpha_2 \ln SPILLTECH_{it-1} + \alpha_3 \ln SPILLSIC_{it-1} + \alpha_4 X_{it}^R + \eta_i^R + \tau_t^R + \nu_{it}^R \qquad (15)$$

This corresponds to equation (9) in our model. Coefficient α_2 (α_3) is positive when R&D of firms close in technology (product) space is strategic complements, and negative when they are strategic substitutes. The user cost of R&D capital is absorbed in the fixed effects and time dummies. To mitigate endogeneity, we lag the key right hand side variables by one year. We also examine specifications that relax the constant returns assumption, using $\ln R$ as the dependent variable and including $\ln Y$ on the right hand side of the equation.

We then estimate the patent equation using a Negative Binomia Model:

$$P_{it} = \exp(\lambda_1 G_{it-1} + \lambda_2 \ln SPILLTECH_{it-1} + \lambda_3 \ln SPILLSIC_{it-1} + \lambda_4 X_{it}^P + \tau_t^P + \nu_{it}^P) \qquad (16)$$

This corresponds to equation (10) in our model. Conditional on own R&D, the coefficient λ_2 captures the spillover effects, and λ_3 should be close to zero. To control for firm fixed effects, we include industry fixed effects and "pre-sample mean scaling" to control for fixed effects (it's computationally demanding to estimate a negative binomial model with firm dummies). We used a long pre-sample history (from 1970 to at least 1980) of patenting behavior to construct the pre-sample average. This can then be used as an initial condition to proxy for unobserved heterogeneity under the assumption that the first moments of all the observables are stationary.

The market value equation is a linearization of the value function introduced by Griliches

[3]The Appendix of BSV provides details of construction of the instrument, and shows that the R&D tax credits are exogenous to changes in economic conditions.

(1981) augmented with our spillover terms:

$$\ln\left(\frac{V}{A}\right)_{it} = \ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it-1}\right) + \gamma_2 \ln SPILLTECH_{it-1} + \gamma_3 \ln SPILLSIC_{it-1} + \gamma_4 X_{it}^{V} + \eta_i^{V} + \tau_t^{V} + \nu_{it}^{V} \tag{17}$$

where V is the market value of a firm, A is the stock of non-R&D assets, G is the R&D stock. The term $\ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it-1}\right)$ is approximated by a sixth order series expansion.

Finally, the productivity equation is:

$$\ln Y_{it} = \varphi_1 \ln G_{it-1} + \varphi_2 \ln SPILLTECH_{it-1} + \varphi_3 \ln SPILLSIC_{it-1} + \varphi_4 X_{it}^{Y} + \eta_i^{Y} + \tau_t^{Y} + \nu_{it}^{Y} \tag{18}$$

This roughly corresponds to equation (12) in our model. The coefficient φ_2 captures two spillover effects: a firm builds on the knowledge of other firms to innovate more and expand its knowledge stock; and it also produces more efficiently using the pool of knowledge as an additional input in their production functions. As in patent equation, conditional on own R&D, R&D of product rivals should have no impact on productivity. However, in practice, we measure output as "real sales" – firm sales divided by an industry price index. Because we do not have information on firm-specific prices, this induces measurement error. If R&D by product market rivals depresses own revenues, the coefficient on *SPILLSIC* may be negative.

4. Data

We use firm-level data from North America CompuStat from 1980 to 2001. We then use the matching built by Hall et al. to match patents from USPTO to CompuStat firms (See NBER data archive and Hall, Jaffe, and Trajtenberg (2001)). They contain all the patents granted between January 1963 and December 1999, and all citations made to these patents between 1975 and 1999. This matching from USPTO patents to CompuStat is the best so far, but it still contains many type 1 and type 2 error given the difficulty of cleaning and disambiguating assignee names in patent applications.

The book value of capital is the net stock of property, plant, and equipment. R&D is used to create R&D capital stocks calculated using a perpetual inventory method with a 15%

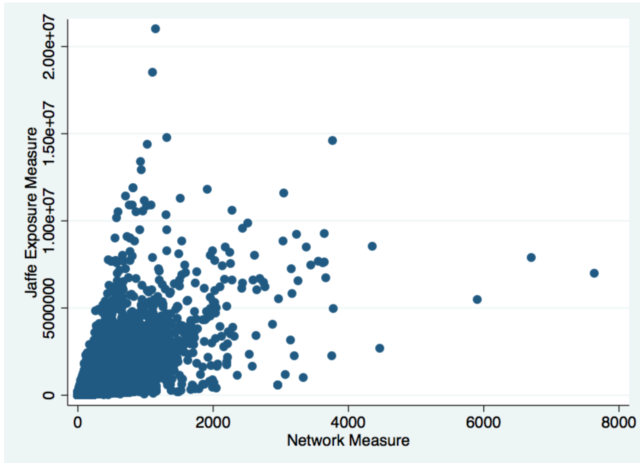
depreciation rate. So the R&D stock, G, in year t is $G_t = R_t + (1 - \delta)G_{t-1}$,where R is the R&D flow expenditure in year t and $\delta = 0.15$. We use deflated sales as our output measure, and industry price deflators were taken from Bartelsman, Becker, and Gray (2000) until 1996 and then the BEA four digit NAICS Shipment Price Deflators thereafter. For Tobin's Q, firm value is the sum of the values of common stock, preferred stock, and total debt net of current assets. The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles other than R&D.

Since our technological distance requires information on patenting, we exclude firms that have no patents between 1963 and 1999, leaving an unbalanced panel of 715 firms. I also exclude patents in three technology classes (1, 395 and 520) that do not exist in the innovation network. The share vectors F is based on the share of patents of each firm over the period 1970 to 1999 in 423 technology classes.[4]

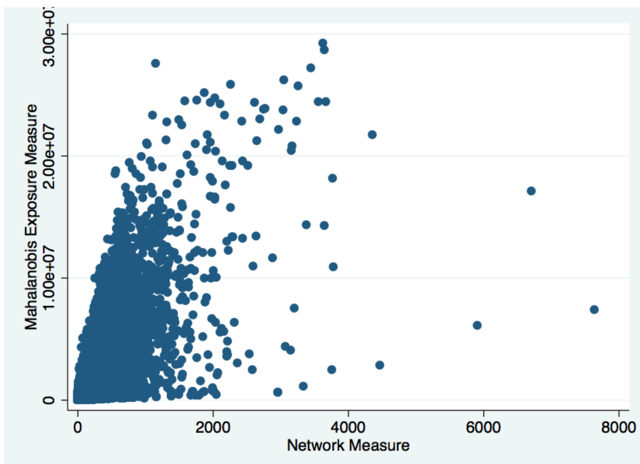
The patent citation matrix (C in equation (1)) is constructed using the citations data used in AAK, which consists of all the patents granted between 1975 and 1984. Since it's different from the time period which we use to construct distance measures, it will induce some measurement errors. Nevertheless, the measurement errors tend to be small as AAK found that patent citation networks are quite stable over time.

Figure 1 compares the network measure with the Jaffe and Mahalanobis measures for $TECH_{ij}$. For each pair of firm, the left figure plots the network measure along with the Jaffe exposure measure, and the right figure plots the network measure along with the Mahalanobis exposure measure. The correlation of network measure with Jaffe measure is 0.79, and with Mahalanobis measure is 0.82. (The correlation between Jaffe and Mahalanobis is 0.90.) This suggests that our network measure is very different from the two measures, and the knowledge spillovers across technology fields though the innovation network is nontrivial.

[4]BSV rounded the percent shares to the nearest integer to reduce memory size, but I didn't do the approximation.



(a) Network and Jaffe



(b) Network and Mahalanobis

Figure 1

5. Empirical results

5.1 R&D equation

Table 1 presents the results for the R&D equation (15). In all specifications we control for log total sales weighted by by SIC matrix and its one-period lag. In Column 1, when we do not include firm fixed effects, both technology spillover *SPILLTECH* and product market spillover *SPILLSIC* have large and significant positive impact on R&D. In Column 2 we include firm fixed effects, and both coefficients get smaller, but still positive and significant. The Hausman test rejects the null of random effects versus fixed effects (p-value$<$0.001). The positive effects indicate that R&D among product rivals and technology neighbors are strategic complements. In Column 3 we use the Mahalanobis measure to calculate technological distance, and in Column 4 we use the network measure defined in Section 2 to calculate technological distance. In both columns *SPILLSIC* remains positive, and a 10 percent increase in R&D of product rivals is associated with 0.6 to 1 percent increase in the firm's R&D intensity; the coefficient on *SPILLTECH* is mildly negative for Mahalanobis measure, and positive for network measure. To relax the constant returns assumption, we use ln(R&D) as the dependent variable and added ln(Sales) to the right hand side, and get very similar results.[5]

In Columns 5 to 7, we treat *SPILLTECH* and *SPILLSIC* as endogenous and use R&D tax credits as instruments. The first stage for both variables are strong. In all three columns, the coefficients on *SPILLTECH* is positive, and is significant for Jaffe and network measures, suggesting that own and technology neighbor's R&D are strategic complements. OLS are biased toward zero; one reason is measurement errors, and mobility of scientists and engineers across firms may result in negative correlation between R&D of firms that innovate in similar technological fields. In the last column, when we are using the network measure, R&D of technology neighbors has very large positive impact on own R&D: a 10 percent increase in *SPILLTECH* leads to 3.7% increase in own R&D. This suggests that own R&D responds strongly to the knowledge stock of "upstream" firms, and a firm invests more on R&D when there is a larger pool of knowledge to build on.

Throughout the last three columns, the coefficient on *SPILLSIC* is negative and insignificant, suggesting that there is very weak strategic effects between own and product market rival's R&D,

[5]For example, when using Jaffe measure, the coefficient (standard error) of *SPILLTECH* is 0.099(0.066), and of *SPILLSIC* is 0.088(0.035).

which supports the assumption that $\mu \approx 0$ in our model. OLS estimates are biased upwards due to common shocks that affect firms in the same industry.

5.2 Patent equation

Table 2 presents the results for the citation-weighted patents equation. The first column shows that spillovers from technology neighbors have a positive and significant impact on patenting, and spillovers from product rivals, which theoretically have zero impact on patenting, has a positive but much smaller coefficient.

In Columns 2 to 4, we control for firm fixed effects by using the Blundell, Griffith, and Van Reenen (1999) method of conditioning on the pre-sample, citation-weighted patents. This method relaxes the strict exogeneity assumption underlying the approach of Hausman, Hall, and Griliches (1984). We also used the approach of Hausman, Hall, and Griliches (1984) to control for firm fixed effects in negative binomial regressions, and the results are similar.[6] For all three measures of technological proximity, the coefficient on *SPILLTECH* is positive and significant, and the coefficient on *SPILLSIC* is close to zero, which is consistent with the theory.

In the last three columns, we treat R&D spillovers as endogenous, and the coefficients don't change much. In all specifications we used citation-weighted patents as the dependent variable, and the results are roughly similar if we use unweighted patent counts: for Jaffe measure, the coefficient on *SPILLTECH* is 0.488 (standard error=0.040), and on *SPILLSIC* is 0.069 (standard error=0.018), which is close to the results in Column 2.

In Column 4 and Column 7, when we use network measure of technological proximity between firms, we get larger effects of *SPILLTECH* than using the other two measures. This is most likely due to smaller measurement errors, since by incorporating the R&D spillovers from "upstream" technological fields, we get a more precise measure of R&D spillovers from technology neighbor firms. In an unreported regression, when we include all three measures as regressors, only the

[6] The coefficient (standard error) on *SPILLTECH* is 0.259(0.021), and on *SPILLSIC* is -0.004(0.012).

coefficient on *SPILLTECH* using the network measure is positive and significant.[7]

5.3 Market value equation

Table 3 shows the results of the market value equation. In Column 1, without the firm fixed effects, both *SPILLTECH* and *SPILLSIC* have a positive effect on firm's market value. The sign of coefficient on *SPILLSIC* turned negative but insignificant once we control for firm fixed effects in Column 2. The Hausman test rejects the null of random effects against fixed effects with p-value equal to 0.058. The R&D spillovers from technologically related firms is positive and significant: a 10% increase in *SPILLTECH* is associated with about 1.7% increase in market value. In Column 3, we estimated fixed effects regression using the Mahalanobis distance measure, and the coefficient on *SPILLTECH* rises substantially. This suggests that the Mahalanobis measure reduces attenuation bias by more accurately weighting the distance between technology fields. In Column 4 we used the network distance measure, and results are similar to the Jaffe distance measure. Columns 5 to 7 present the results of the 2SLS regressions using R&D tax credits as instruments. The coefficients on *SPILLTECH* are positive and significant, and have larger magnitudes than OLS regressions. Coefficients are similar for all three distance measures, and largest for the Mahalanobis measure.

Throughout the regressions, the coefficient on *SPILLSIC* is negative, but the product market rivalry effects of R&D on market value is not statistically significant. The third row shows that higher R&D investments increases a firm's market value. A 10 percent increase in own R&D stock increases market value by 3 percent, as compared to a 5 to 7 percent increase in market value caused by a 10 percent increase in R&D spillovers from technologically close firms.

[7]The coefficient (standard error) of *SPILLTECH* constructed using Jaffe, Mahalanobis, and network measure is 0.154(0.128), 0.160(0.170), and 0.519(0.092).

5.4 Productivity equation

Finally, Table 4 summarizes the results for the productivity equation. In Column 1, without firm fixed effects, both *SPILLTECH* and *SPILLSIC* have negative coefficients. In Column 2, when we control for firm fixed effects, *SPILLTECH* has a positive effect on productivity, and *SPILLSIC* has nearly zero effect on productivity, which is consistent with the theory. The Hausman test again rejects random effects with p-value less than 0.001.

In Column 3 we use the Mahalanobis distance measure, and in Column 4 we use the network distance measure. As in market value equations, the coefficient on *SPILLTECH* is the largest when we use the Mahalanobis measure.

In the last three columns, we treat the R&D spillovers as endogenous, and the results don't change much. Notably, the coefficient on *SPILLTECH* is no longer significant when we use the network distance measure and instrument for the R&D spillovers.

5.5 Summary of empirical results

In Table 1 to Table 4 we redo the empirical analysis of BSV using the Jaffe and Mahalanobis exposure distance measure and the network distance measure constructed in Section 2. The results using Jaffe and Mahalanobis exposure measures are similar to the results in BSV which uses Jaffe and Mahalanobis correlation measures. The results are consistent with our model: higher R&D by firms close in technology space is associated with higher patenting, market value and productivity, while higher R&D by firms close in product space (weakly) diminishes market value and has no effect on patenting or productivity. Own R&D is strategic complements with R&D by firms operating in similar or "upstream" technology fields, and is neither strategic substitutes nor strategic complements with R&D by product market rivals.

In R&D and patent equations, the coefficient on *SPILLTECH* is the largest when using the network distance measure; in market value and productivity equations, the coefficient on *SPILLTECH* is the largest when using the Mahalanobis measure. Higher R&D of firms operating in upstream technological fields increases a firm's own R&D and patenting, but has much smaller effects on productivity or market value.

These can be interpreted using our model. In the model there are two kinds of spillovers from technologically connected firms: one is "innovation" spillover (σ_i and γ in equation (7)), which leads to higher innovation output due to knowledge accumulation; the other is "production" spillover (ψ in equation (8)), which leads to higher productivity due to technology adoption (note that the "innovation spillover" γ does not appear directly in productivity equation (12)). The pool of knowledge generating the "innovation" spillover is more precisely measured by network distance measure, while the pool of knowledge generating the "production" spillover is better characterized by the Mahalanobis distance measure. For example, communications is an upstream technology field of computer technology, and R&D by AT&T would lead to higher patenting of a firm producing computers, but may not have direct effects on productivity of these firms. On the other hand, suppose technology A and B are complements in production, R&D of firm 1 in technology A leads to higher productivity of firm 2 which innovates in the technology B. When calculating *SPILLTECH* for firm 2, Mahalanobis measure would take into account firm 1's R&D, which would be ignored by network measure if there is no patent citations from technology B to technology A.

6. Robustness and Extensions

6.1 Decomposing within-class and cross-class technology spillovers

Among the three distance measures, Jaffe measure only considers technology spillovers within technology classes, while Mahalanobis and network measure also considers technology spillovers across technology classes: Mahalanobis considers spillovers from closely related fields, and network measure considers "upstream" fields that patents in the technology field cite from. One concern is that the effects of *SPILLTECH* in regressions using the Malahanobis and network distance measures are driven by within-class technology spillovers.

To assess the importance of technology spillovers across technology fields we decompose the

Mahalanobis measure into within-class (diagonal) and cross-class (non-diagonal) components:

$$TECH_{ij}^{M} = n_i F_i \Omega F_j' = n_i F_i F_j' + n_i F_i (\Omega - I) F_j' = TECH_{ij}^{J} + TECH_{ij}^{M-Cross}$$

Note that the within-class component is exactly the Jaffe distance measure. We can also do the same decomposition for the network distance measure.

Table 5 presents the results for within and cross class technology spillovers separately. We report OLS results, and using tax credits as instruments also yields similar results. Column 1 repeats the results for Jaffe distance measure. Column 2 uses only the cross class component of network measure as the measure of *SPILLTECH*. The cross class technology spillovers alone still have a positive and significant impact on R&D, patenting, market value and productivity, which is of similar magnitude as the impact of within-class technology spillovers. For instance, in panel A, a 10 percent increase in within class R&D spillovers is associated with a 1 percent increase in own R&D intensity, while a 10 percent increase in cross class R&D spillovers is associated with a 1.5 percent increase in own R&D intensity.

In Column 3 we include both within-class (same as Jaffe) and cross class component of R&D spillovers measured using network measure. In R&D equation, the coefficient on within-class *SPILLTECH* is small and insignificant, and the coefficient on cross-class *SPILLTECH* is positive and significant, suggesting that R&D responds strongly to R&D by firms operating in "upstream" technology fields. This is consistent with the finding in AAK that about half of the patent citations are from outside the technology class. Cross-class spillovers also has a larger impact on market value and patenting than within-class spillovers. However, cross-class spillovers has a smaller impact than within-class spillovers on productivity, since the cross-class citation patterns fail to capture the "production" spillovers.

In the last column, we include cross-class component of both network and Mahalanobis distance measure to see which is a better characterization of the spillovers across technology fields. Not surprisingly, the network measure has the largest coefficient in R&D and patent equations, and the Mahalanobis measure has the largest coefficient in market value and productivity equations. In R&D and patent equations, within-class and cross-class spillovers both have positive and significant impact, and are of similar magnitudes. However, the coefficient on within-class spillovers is negative and significant in market value equation, and is insignificant in productivity equation. One reason is that firms that are close in technology space using Jaffe measure have a lot of overlap with firms that are close in technology space using Mahalanobis measure (correlation between Jaffe and Mahalanobis measure is 0.9), so *SPILLTECH* using Mahalanobis measure is highly correlated with *SPILLTECH* using Jaffe measure even after subtracting the within-class component.

6.2 Using patent stock as knowledge stock

So far we have followed BSV and use the R&D stock to approximate knowledge stock k_t. R&D may not measure knowledge stock accurately, for example, some firms may possess a big knowledge stock despite little investment in R&D if they are very productive in research or they benefit from a lot of spillovers from other firms. A more direct measure of knowledge stock would be to use the stock of patents owned by a firm, and spillovers can be calculated as:

$$SPILLTECH_{it}^{N} = \sum_{j \neq i} TECH_{ij} P_{jt}$$

$$SPILLSIC_{it}^{N} = \sum_{j \neq i} SIC_{ij} P_{jt}$$

where P_{jt} is the accumulated unweighted number of patents of firm j at year t, and is calculated using perpetual inventory method with a 15% depreciation rate. The patent stock may not accurately measure the knowledge stock either, as part of knowledge stock (like scientists, management practices) are not captured by number of patents.

The results are presented in Table 6. In Column 1 to Column 3, we calculate *SPILLTECH* using all the three distance measures respectively, and in the last column all three measures are included as regressors. In R&D equation, only *SPILLTECH* using the network distance measure has positive and significant coefficient, suggesting that firms' R&D responds positively to patent stock of firms operating in "upstream" technological fields but not patent stock of firms operating in similar technological fields.

The overall results are very similar to using R&D stock to measure knowledge stock. All three measures of *SPILLTECH* has a positive and significant effect on patenting, market value and productivity. The network measure performs the best in patent equation, while the Mahalanobis measure performs the best in market value and productivity equations.

6.3 Persistence of technology spillovers over time

In this subsection we study the effects of technology spillovers over time. Technology diffusion happens gradually, especially if across technology fields. AAK shows that in the first year after invention, 62% of the downstream citations come from the same patent class, and 81% are from the same patent category; after ten years, only 51% of citations are from the same patent class, and 75% from the same category.

In Table 7, we use the measure of R&D spillovers *SPILLTECH* lagged by 1 year, 5 years and 10 years as regressors separately. Each element in the table is a separate OLS regression (regressions using IV yield qualitatively similar results). The effect of *SPILLTECH* on own R&D becomes insignificant after five or ten years. Nevertheless, the impact of *SPILLTECH* on patenting, market value and productivity tend to persist after five or ten years. In patent equations, a one percent increase in R&D spillovers from firms in upstream and similar technology fields is associated with a nearly one percent increase in patenting even after 10 years. This implies that technology diffusion is slow and R&D has a long-lasting impact on future innovation.

In market value equation, the effect of *SPILLTECH* more than doubled after 10 years, suggesting that market value reacts slowly to changes in innovation. In productivity equations, *SPILLTECH* using the network measure has a smaller coefficient than the other two measures when lagged by one year, but has a larger coefficient than other measures when lagged by ten years. This is consistent with the view that "innovation" spillovers across technology fields takes a longer time to have effects on productivity than "production" spillovers where new technologies can be adopted immediately.

In the last row of each panel, I used the R&D spillovers of five years later as a falsification exercise. In R&D, market value and productivity equations, all the coefficients on *SPILLTECH* become statistically insignificant except for one case (Mahalanobis measure in productivity equation). *SPILLTECH* still has a positive and significant impact on patenting, but the magnitude is less than one third of the coefficients on lags of R&D spillovers. This confirms that the effect of R&D spillovers from technologically close firms on firm outcomes that we found is credible and not purely driven by common shocks.

7. Which Firms Generate and Receive the Largest Spillovers?

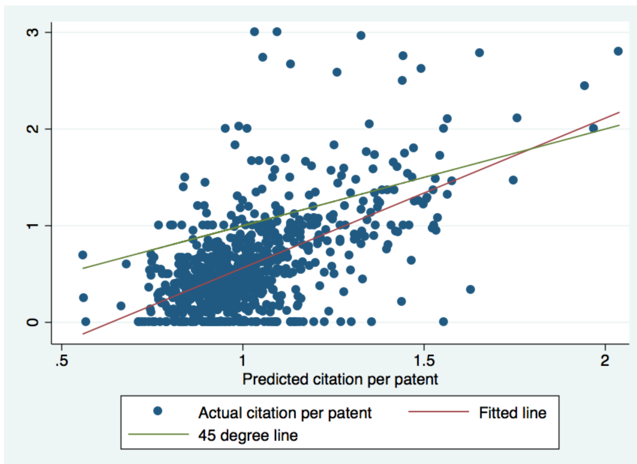
The network measure gives us a simple measure of the spillover of a firm's knowledge stock to other firms: the predicted number of times the firm's patents get cited by other patents. From equation (1) we can write it as:

$$CITE_i = \sum_{j \neq i} TECH^N_{ji} = \sum_{j \neq i} n_j F_j C F_i' \approx \sum n_j F_j C F_i' = \tilde{C} F_i' \tag{19}$$

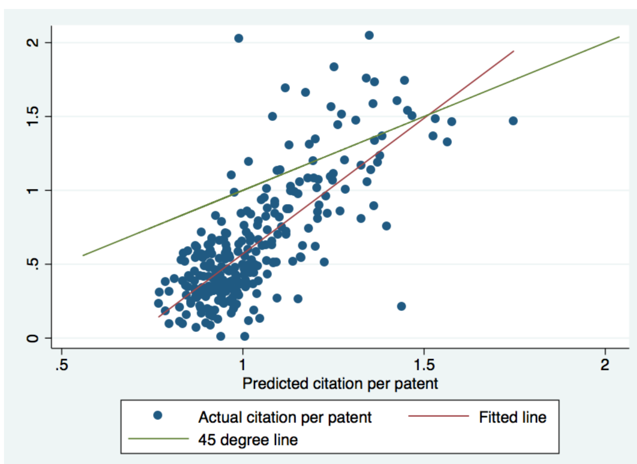
where $\tilde{C}_{\tau\tau'} = N_\tau C_{\tau\tau'}$. The predicted average citations of a firm's patents is determined only by a firm's distribution of technology classes, and it is larger when the firm innovates in more "upstream" technology classes.

Figure 2 plots the actual average citations per patent along with the predicted citations per patent of each firm. The left panel contains all 796 firms in the sample. The trending line shows that the actual citations per patent increase by 1.5 when the predicted citations per patent increase by one. This specification explains about 34% of the variation in actual citations per patent. The actual citations per patent is below the 45 degree line because the number of citations is truncated by the sample period, and the distribution of number of citations is right skewed. Since the average citations is more volatile for small firms, the right panel of Figure

2 contains 277 firms that have more than 100 patents. The actual average citations is more aligned with predicted citations, and the technology class distribution of a firm accounts for 56% of the variation in average citations per patent.



(a) All firms



(b) Firms with more than 100 patents

Figure 2

BSV claims that smaller firms generate less spillovers because they innovate in technological niches where few other firms innovate in. In Table 8 we also divide firms into quartiles by employment size and calculate the mean measures for spillovers within each quartile. In line with BSV's conclusion, the average Jaffe and Mahalanobis measure of *TECH* increases with firm size. Nevertheless, both the network measure and the cross-class component of network measure are largest for the smallest quartile. This suggests that although smaller firms operate in less technological fields and have less overlap with other firms, they are also more likely to operate in more "upstream" technological fields, which generates large knowledge spillovers to the other firms. The largest firms also generate more spillovers than medium-sized firms. This is consistent with some literature on reallocation which finds that smaller (and younger) firms are more innovative and an R&D subsidy to entrants and small firms is welfare-improving.

There are some other interesting insights from using the network measure. Using the citation network matrix C, we can rank all the technology classes from "upstream" to "downstream" using the average number of citations each patent in that class gets. For example, the most upstream technology field is "Data Processing: Artificial Intelligence": each patent in this field are cited 5.3 times within 10 years, half from within the field and half from outside the field. Nearly all the top 10 upstream technology fields are in the computer software and data processing category. We can also rank the firms from technologically upstream to downstream based on their technology field distributions. Among the top 100 upstream firms that generates the largest spillovers, more than 70% are from five three-digit (SIC) industries: Surgical, Medical, and Dental Instruments and Supplies (384), Electronic Components and Accessories (367), Computer and Office Equipment (357), Drugs (283), and Computer Programming, Data Processing, and other Computer Related Services (737).

In Table 9 we divided firms into quantiles based on innovation intensity. The innovation intensity is calculated as the total number of patents from from 1970 to 1999 divided by the number of employees. Firms with higher innovation intensity are on average smaller, and generated larger spillovers to other firms. Comparing Column 3 and Column 4, the firms in the highest quantile and second highest quantile have similar nearly the same *TECH* on average when using Jaffe and Mahalanobis measure, but the highest quantile have much larger *TECH* measured by the network measure. This suggests that firms that are most intensive in research and innovation tend to also research more in upstream technological fields.

On the other hand, to study the spillovers a firm receives, consider the knowledge production function from Section 3:

$$k_i^t = \phi(r_i^t, k_i^{t-1}, k_\tau^{t-1}) = \phi(r_i^t, k_i^{t-1}, T_i\mathbf{k}^{t-1})$$

The spillover term is:

$$T_i k^{t-1} = \sum_{j\neq i} TECH_{ij} k_j^{t-1} \propto \sum_{j\neq i} F_i C F_j' k_j^{t-1} \approx F_i C(\sum_j F_j' k_j^{t-1}) = (\sum_j k_j^{t-1}) F_i C F_{all}'$$

where F_{all} is the technology class distribution of all the firms.

The term $F_i C F_{all}'$ is the measure of the technology spillovers of all other firms' R&D on firm i. We calculated this measure for all firms in the CompuStat sample, and Table 8 and Table 9 presents the results for firm quantiles of employment and innovation intensity respectively . Loosely speaking, the predicted citations per patent measures how "upstream" in the technology space the firm is, and the spillovers from other firms measures how technologically "downstream" the firm is. Since spillovers within technology classes are hard to interpret, we also included measures for only cross-class spillovers.

Last two rows of Table 8 shows that smaller firms receive more spillovers from other firms than large firms. Table 9 suggests that firms with lower innovation intensity receive more spillovers from other firms. This may be explained by endogenous technology choices. If firms could direct their research and choose the technology class distribution F_i, then for small firms and firms with low R&D intensity, spillovers from other firms are more important in the knowledge production, and they benefit more from choosing more "downstream" technology fields.

Table 8 and Table 9 show that small firms are the largest sources and the largest receivers of technology spillovers, since they populate in the most upstream and downstream technological fields. This comes from the asymmetry of the network measure. In contrast, in BSV small firms operate in technological niches, so they would generate and receive the smallest spillovers. Our result is similar to the findings of Manresa (2013), who estimated unknown network relationships between firms using the same data, and found that sources of spillovers are on average small firms with low employment and market value, and have higher R&D intensity and patent citations.

8. Conclusion

In this paper we develop a new measure of technological distance between firms based on the patent citations network in AAK. Unlike Jaffe and Mahalanobis measure, the network measure is asymmetric: firms doing research in upstream technology classes generate knowledge spillovers to firms doing research in downstream technology classes because new innovations builds on past achievements, but not vice versa.

We then use this measure to estimate the effects of R&D of firms close in technology space or product space on firm's R&D, patenting, market value and productivity. We do not find significant product rivalry effect, but R&D spillovers from firms close in technology space have a positive and significant impact on market value, productivity and patenting. When using the network distance measure we constructed, the R&D spillovers from upstream firms also has a positive and significant impact on R&D. The spillovers using the network measure also have the largest impact on patenting, though the spillovers using the Mahalanobis measure have the largest impact on market value and productivity. This together with our model suggests that the network measure is a more accurate measure of the technology spillovers that future innovations builds on, while Mahalanobis measure better captures technology adoption in production.

We view this as a first step in understanding the micro-foundations of the innovation network. While AAK established the network relationships between technology classes, little is known of how firms innovating in different technology classes interact with each other and how this affects the aggregate innovations in the economy. By using the network measure instead of Jaffe or Mahalanobis measure, we put firms on a directed innovation network rather than a technology space. Firms' R&D decisions form a game over the innovation network, and we already presents some evidence that firm's R&D responds positively to R&D of upstream firms.

Studying firm interactions over the innovation network is important in many ways. First, we can identify which firms generate the largest spillovers to other firms and how large the spillovers are, which is crucial for designing R&D tax policies and is the main motivation of most studies on R&D spillovers. Second, it can help us understand better the aggregate effect of shocks on innovation by looking at how shocks are transmitted through the innovation network to upstream and downstream firms. For example, if some shocks (for example, Chinese imports competition or financial crisis) affects the R&D and innovation of a subset of firms adversely, then the R&D and innovation of firms operating in downstream technology fields of the affected firms will suffer too.

One future direction would be to refine the measure by backing out the unknown network relationships between firms, like Manresa (2013), since some of the knowledge flows are not captured by patent citations. It would also be interesting to compare the network relationship identified using the firm outcomes and the network measure constructed in this paper and other measures of technological distance.

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Table 1
R&D Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS
Distance measure	Jaffe	Jaffe	Malahanobis	network	Jaffe	Malahanobis	network
ln(*SPILLTECH*)$_{t-1}$	0.438	0.099	-0.008	0.187	0.192	0.085	0.370
	(0.029)	(0.068)	(0.087)	(0.076)	(0.105)	(0.113)	(0.104)
ln(*SPILLSIC*)$_{t-1}$	0.369	0.084	0.106	0.068	-0.055	-0.008	-0.104
	(0.013)	(0.035)	(0.034)	(0.034)	(0.073)	(0.070)	(0.069)
					IV 1st stage F-tests		
ln(*SPILLTECH*)$_{t-1}$					220.6	795.6	383.4
ln(*SPILLSIC*)$_{t-1}$					30.6	40.5	24.4
Firm fixed effects	no	yes	yes	yes	yes	yes	yes
Number of obs	8,579	8,579	8,579	8,579	8,579	8,579	8,579

Table 2
Patent Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin.	NB IV	NB IV	NB IV
Distance measure	Jaffe	Jaffe	Malahanobis	network	Jaffe	Malahanobis	network
ln(*SPILLTECH*)$_{t-1}$	0.548	0.621	0.709	0.841	0.622	0.718	0.848
	(0.037)	(0.040)	(0.045)	(0.049)	(0.042)	(0.046)	(0.050)
ln(*SPILLSIC*)$_{t-1}$	0.069	0.085	0.064	0.037	0.083	0.057	0.029
	(0.023)	(0.023)	(0.022)	(0.023)	(0.025)	(0.023)	(0.024)
ln(R&D Stock)$_{t-1}$	0.048	0.040	0.068	0.050	0.041	0.044	0.072
	(0.032)	(0.035)	(0.033)	(0.034)	(0.035)	(0.035)	(0.034)
					IV 1st stage F-tests		
ln(*SPILLTECH*)$_{t-1}$					229.7	490.2	205.5
ln(*SPILLSIC*)$_{t-1}$					58.9	13.8	14.0
Pre-sample FE	no	yes	yes	yes	yes	yes	yes
Number of obs	9,046	9,046	9,046	9,046	9,046	9,046	9,046

Table 3
Market Value Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS
Distance measure	Jaffe	Jaffe	Malahanobis	network	Jaffe	Malahanobis	network
ln(*SPILLTECH*)$_{t-1}$	0.061	0.171	0.510	0.204	0.547	0.722	0.523
	(0.017)	(0.082)	(0.105)	(0.090)	(0.129)	(0.128)	(0.132)
ln(*SPILLSIC*)$_{t-1}$	0.062	-0.024	-0.036	-0.025	-0.039	-0.028	-0.030
	(0.006)	(0.026)	(0.025)	(0.026)	(0.071)	(0.068)	(0.071)
ln(R&D Stock/Capital)$_{t-1}$	0.644	0.323	0.330	0.312	0.316	0.336	0.294
	(0.138)	(0.174)	(0.174)	(0.174)	(0.174)	(0.174)	(0.174)
					IV 1st stage F-tests		
ln(*SPILLTECH*)$_{t-1}$					195.3	946.2	411.6
ln(*SPILLSIC*)$_{t-1}$					40.9	41.3	35.9
Firm fixed effects	no	yes	yes	yes	yes	yes	yes
Number of obs	12,561	12,561	12,561	12,561	12,561	12,561	12,561

Table 4
Productivity Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS
Distance measure	Jaffe	Jaffe	Malahanobis	network	Jaffe	Malahanobis	network
ln(*SPILLTECH*)$_{t-1}$	-0.026	0.141	0.237	0.116	0.128	0.185	0.031
	(0.009)	(0.041)	(0.053)	(0.045)	(0.074)	(0.072)	(0.066)
ln(*SPILLSIC*)$_{t-1}$	-0.015	-0.006	-0.006	-0.002	0.025	0.019	0.064
	(0.004)	(0.012)	(0.011)	(0.012)	(0.056)	(0.055)	(0.054)
ln(R&D Stock)$_{t-1}$	0.061	0.043	0.042	0.044	0.042	0.042	0.043
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
					IV 1st stage F-tests		
ln(*SPILLTECH*)$_{t-1}$					84.8	1082.9	440.9
ln(*SPILLSIC*)$_{t-1}$					17.2	61.9	54.5
Firm fixed effects	no	yes	yes	yes	yes	yes	yes
Number of obs	9,949	9,949	9,949	9,949	9,949	9,949	9,949

Table 5
Comparing Within and Cross Class Technology Spillovers

	(1)	(2)	(3)	(4)
A. R&D Equation				
ln(*SPILLTECH*)$_{t-1}$-Jaffe	0.099		0.017	0.278
	(0.068)		(0.116)	(0.126)
ln(*SPILLTECH*)$_{t-1}$-network cross		0.152	0.135	0.358
		(0.087)	(0.147)	(0.155)
ln(*SPILLTECH*)$_{t-1}$-Mahalanobis cross				-0.661
				(0.154)
ln(*SPILLSIC*)$_{t-1}$	0.084	0.081	0.080	0.071
	(0.035)	(0.034)	(0.035)	(0.035)
B. Patent Equation				
ln(*SPILLTECH*)$_{t-1}$-Jaffe	0.621		0.370	0.269
	(0.040)		(0.052)	(0.101)
ln(*SPILLTECH*)$_{t-1}$-network cross		0.757	0.426	0.363
		(0.048)	(0.064)	(0.082)
ln(*SPILLTECH*)$_{t-1}$-Mahalanobis cross				0.163
				(0.144)
ln(*SPILLSIC*)$_{t-1}$	0.085	0.078	0.048	0.047
	(0.023)	(0.024)	(0.022)	(0.022)
C. Market Value Equation				
ln(*SPILLTECH*)$_{t-1}$-Jaffe	0.171		-0.063	-0.422
	(0.082)		(0.125)	(0.161)
ln(*SPILLTECH*)$_{t-1}$-network cross		0.356	0.411	0.080
		(0.106)	(0.160)	(0.167)
ln(*SPILLTECH*)$_{t-1}$-Mahalanobis cross				0.990
				(0.209)
ln(*SPILLSIC*)$_{t-1}$	-0.024	-0.029	-0.026	-0.013
	(0.026)	(0.025)	(0.026)	(0.027)
D. Productivity Equation				
ln(*SPILLTECH*)$_{t-1}$-Jaffe	0.141		0.132	0.027
	(0.041)		(0.057)	(0.076)
ln(*SPILLTECH*)$_{t-1}$-network cross		0.135	0.015	-0.140
		(0.052)	(0.072)	(0.076)
ln(*SPILLTECH*)$_{t-1}$-Mahalanobis cross				0.354
				(0.108)
ln(*SPILLSIC*)$_{t-1}$	-0.006	0.0004	-0.006	-0.003
	(0.012)	(0.012)	(0.012)	(0.012)

Table 6
Using Patent Stock as Knowledge Stock

	(1)	(2)	(3)	(4)
A. R&D Equation				
$\ln(\mathit{SPILLTECH})_{t-1}$-Jaffe	-0.001			-0.194
	(0.038)			(0.089)
$\ln(\mathit{SPILLTECH})_{t-1}$-Mahalanobis		0.017		-0.005
		(0.051)		(0.112)
$\ln(\mathit{SPILLTECH})_{t-1}$-network			0.065	0.252
			(0.041)	(0.071)
$\ln(\mathit{SPILLSIC})_{t-1}$	0.026	0.023	0.014	0.020
	(0.018)	(0.017)	(0.017)	(0.017)
B. Patent Equation				
$\ln(\mathit{SPILLTECH})_{t-1}$-Jaffe	0.599			0.247
	(0.041)			(0.124)
$\ln(\mathit{SPILLTECH})_{t-1}$-Mahalanobis		0.663		-0.013
		(0.045)		(0.159)
$\ln(\mathit{SPILLTECH})_{t-1}$-network			0.836	0.599
			(0.050)	(0.092)
$\ln(\mathit{SPILLSIC})_{t-1}$	0.111	0.089	0.043	0.035
	(0.025)	(0.024)	(0.024)	(0.023)
C. Market Value Equation				
$\ln(\mathit{SPILLTECH})_{t-1}$-Jaffe	0.077			-0.549
	(0.071)			(0.189)
$\ln(\mathit{SPILLTECH})_{t-1}$-Mahalanobis		0.251		0.630
		(0.105)		(0.242)
$\ln(\mathit{SPILLTECH})_{t-1}$-network			0.175	0.280
			(0.082)	(0.182)
$\ln(\mathit{SPILLSIC})_{t-1}$	0.017	0.009	0.008	0.018
	(0.022)	(0.021)	(0.022)	(0.022)
D. Productivity Equation				
$\ln(\mathit{SPILLTECH})_{t-1}$-Jaffe	0.129			0.030
	(0.037)			(0.099)
$\ln(\mathit{SPILLTECH})_{t-1}$-Mahalanobis		0.181		0.118
		(0.050)		(0.119)
$\ln(\mathit{SPILLTECH})_{t-1}$-network			0.138	0.026
			(0.041)	(0.073)
$\ln(\mathit{SPILLSIC})_{t-1}$	0.014	0.016	0.015	0.014
	(0.013)	(0.013)	(0.013)	(0.013)

Table 7
Effects of Spillovers Over Time

	R&D	Patent	Market Value	Productivity
A. Network				
$\ln(SPILLTECH)_{t-1}$	0.187	0.841	0.204	0.116
	(0.076)	(0.049)	(0.090)	(0.045)
$\ln(SPILLTECH)_{t-5}$	0.093	0.980	0.331	0.069
	(0.083)	(0.059)	(0.111)	(0.054)
$\ln(SPILLTECH)_{t-10}$	0.147	0.945	0.696	0.171
	(0.142)	(0.075)	(0.282)	(0.098)
$\ln(SPILLTECH)_{t+5}$	0.169	0.237	-0.022	-0.120
	(0.159)	(0.025)	(0.088)	(0.175)
B. Jaffe				
$\ln(SPILLTECH)_{t-1}$	0.099	0.621	0.171	0.141
	(0.068)	(0.040)	(0.082)	(0.041)
$\ln(SPILLTECH)_{t-5}$	0.039	0.724	0.424	0.110
	(0.074)	(0.051)	(0.101)	(0.050)
$\ln(SPILLTECH)_{t-10}$	0.107	0.662	0.753	0.166
	(0.127)	(0.068)	(0.270)	(0.097)
$\ln(SPILLTECH)_{t+5}$	0.202	0.251	-0.082	0.090
	(0.181)	(0.024)	(0.080)	(0.187)
C. Mahalanobis				
$\ln(SPILLTECH)_{t-1}$	-0.008	0.709	0.510	0.237
	(0.087)	(0.045)	(0.105)	(0.053)
$\ln(SPILLTECH)_{t-5}$	-0.018	0.825	0.735	0.109
	(0.090)	(0.055)	(0.123)	(0.062)
$\ln(SPILLTECH)_{t-10}$	0.050	0.760	1.036	0.124
	(0.161)	(0.074)	(0.230)	(0.119)
$\ln(SPILLTECH)_{t+5}$	0.123	0.252	-0.061	0.387
	(0.219)	(0.024)	(0.127)	(0.198)

Table 8
Average Measures of Spillovers in Firm Size Quartiles

Quartile	1	2	3	4
Median number of employees	685	3,398	10,442	50,000
Avg. Jaffe *TECH*	0.027	0.031	0.035	0.050
Avg. Malahanobis *TECH*	0.105	0.121	0.143	0.213
Avg. Predicted average citations per patent (Network TECH)	1.054	1.000	0.994	1.010
Avg. Cross-class network TECH	5.393	5.104	5.143	5.269
Avg. spillovers from all other firms	1.183	1.110	1.107	1.088
Avg. cross-class spillovers from all other firms	0.577	0.534	0.54	0.515

Note: the number of employees is measured at the year with the maximum number of employees.

Table 9
Average Measures of Spillovers in Quartiles of Innovation Intensity

Quartile (by innovation intensity)	1	2	3	4
Median number of patents	5	25	110	191
Median number of employees	11,029	4,791	5,700	2,727
Avg. Jaffe *TECH*	0.026	0.033	0.042	0.042
Avg. Malahanobis *TECH*	0.096	0.131	0.174	0.180
Avg. Predicted average citations per patent (Network *TECH* normalized)	0.97	0.993	1.010	1.085
Avg. Cross-class network *TECH*	4.993	5.044	5.201	5.674
Avg. spillovers from all other firms	1.153	1.111	1.099	1.126
Avg. cross-class spillovers from all other firms	0.597	0.537	0.520	0.512

Note: innovation intensity is measured by the number of patents divided by the number of employees.