Research Policy xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Scientific linkages and firm productivity: Panel data evidence from Taiwanese electronics firms☆

Jong-Rong Chen[a,b,c], Kamhon Kan[a,d,*], I-Hsuan Tung[a]

[a] Graduate Institute of Industrial Economics, National Central University, Jhongli 320, Taiwan
[b] Research Center for Humanities and Social Sciences, Academia Sinica, Taipei 115, Taiwan
[c] Public Economics Research Center, National Taiwan University, Taipei 106, Taiwan
[d] Institute of Economics, Academia Sinica, Taipei 115, Taiwan

ARTICLE INFO

Article history:
Received 31 May 2015
Received in revised form 30 March 2016
Accepted 30 March 2016
Available online xxx

JEL classification:
O34
O31
O47

Keywords:
Patent citation
Scientific discoveries
R&D spillover
Productivity

ABSTRACT

Using a panel of electronics firms listed on the Taiwan Stock Exchange, this paper explores the spillover of scientific research to the private sector by looking at the impact of the intensity a patent's backward citation of scientific publications relative to citation of other patents on the patent-owning firm's productivity. To identify the causal effect, we use measures of a firm's financial constraints as instrumental variables to account for the potential endogeneity of scientific citation intensity of a patent. The empirical results suggest that the citation of scientific publications by a patent has a strong and positive effect on the patent-owning firm's productivity.

1. Introduction

Knowledge is a public good, and it is likely that there are spillovers from academic science to commercial firms. Nelson (1986) survey research managers and find that university research is an important source of innovation in some industries. Jaffe (1989) and Adams (1990) show the importance of basic science for economic growth. Acs et al. (1992) find significant externalities from academic research on privative R&D and patenting (Cassiman et al., 2008). Mansfield (1991) and Cohen et al. (2002) also find that academic research is important for industrial innovation. Overall, findings by these studies show that knowledge spillovers from academia to industry have an impact on firms' abilities to innovate.

There are many examples of linkages between academic research and innovations by firms—university-industry collaboration (Zucker et al., 2002; Zucker and Darby, 2001), industry financing university research (OECD, 2004), university licensing (Thursby and Thursby, 2002), and citations to university patents (Trajtenberg et al., 1997), to name a few. An important example of spillovers from academic research to the private sector is the referencing of scientific papers by patents developed by firms (see Narin et al., 1997; and Hicks et al., 2001). For firms, academic research is a very important source of knowledge, a view also held by Jaffe et al. (2002). It leads firms into new areas of innovation and subsequently to new production processes and products. Additionally, academic science enables firms to circumvent needless experimentation. This, in turn, allows them to focus on only the most rewarding avenues of research. Branstetter and Ogura (2005) also indicate that basic science can open new research areas for applied researchers, as well as increase the level of applied research effort and its productivity. All these imply that the spillovers of knowledge from academic research lead to an increase in firms' research productivity (Evenson and Kislev, 1976; Gambardella, 1992).

There is a persistent rise in patents' citations of academic publications. For instance, Narin et al. (1997) report a threefold

☆ We would like to thank the editor Professor Keun Lee and two anonymous referees for constructive comments and suggestions. Partial financial support by the Ministry of Science and Technology of Taiwan to Kamhon Kan through grant 102-2410-H-001-002-MY3 and to Jong-Rong Chen through grant 103-2410-H-008-007-MY2 is gratefully acknowledged.

* Corresponding author at: 128, Section 2, Academia Road, Taipei, 11529, Taiwan.
E-mail address: kk@sinica.edu.tw (K. Kan).

http://dx.doi.org/10.1016/j.respol.2016.03.023
0048-7333/© 2016 Published by Elsevier B.V.

increase in the number of citations of academic literature in industrial patents in the United States during the mid-1990s. They also point out that 73% of the scientific articles cited by industry patents were authored at academic, governmental, and other public institutions.[1] Branstetter and Ogura (2005) show that there has been a rapid increase in citations of scientific articles in patents granted in the U.S. from the mid-1980s until the late 1990s. This increase is well above the increases in the U.S.'s R&D expenditure and the global output of scientific articles. Particularly, while the former increased by nearly 40% and the latter by 13%, scientific references of patent increased by more than 13-fold. This could mean that publicly funded science generated significant spillovers to industrial innovation during this period. Therefore, it would be interesting to see whether these knowledge spillovers from academia to the private sector bring about a contribution to firm productivity.

In addition to referencing academic works, each patent cites other previous patents (i.e., backward patent citations), which is another important knowledge source. Some researchers regard these patent citations as indicative of knowledge spillovers between innovative technologies of firms. For example, Nadiri (1993) indicates that the disclosure of new technologies in patents allows competitors to lower the cost of research by "working around" past patents. Reinganum (1989) and Cockburn and Henderson (1994) argue that firms may benefit from their competitors' research efforts, and knowledge spillovers encourage intellectual exchanges between research teams. Patent citations are basically the "paper trails" of these spillovers among firms (Fung, 2005). Fung (2005) regards backward patent citations as an indication of knowledge spillover, and finds that the intra- and inter-industry spillovers can improve firms' productivity growth. The findings of Deng (2008) suggest that knowledge spillovers received by firms through citation of previous patents bear substantial economic value. Furthermore, those that lag behind can receive benefits from knowledge spillover from leaders in the field, allowing the followers to catch up with the leaders. Peri (2004) believes that patent citations form links between inventions that reveal a learning process at the technological frontier. The above studies suggest that patent citations are a good measure for inter-firm knowledge spillovers.

There exist other views on the implications of a patent's citation of previous patents, arguing that citing more previous patents may imply that the citing patent is less original, especially when the patents cited are important ones (Jaffe et al., 2002). This is because existing patents represent previously discovered technological knowledge in the process of technology development, a patent citing too many previous patents may implies that it does not have very much novel contribution or it is low in creativity (see also Trajtenberg et al., 1997). Also, it is the legal duty for a firm to cite previous patents when it files a patent application for its inventions, such that the citation of previous patents may not reflect spillovers of knowledge.[2]

The above discussion suggests that while the backward citation of patents may or may not be interpreted as spillovers of knowledge among firms, the citation of scientific publications represents the flow of knowledge from academia to industry. However, there are not many studies on how the citation of scientific publications by a patent affects the patent-owning firm's productivity. Most of the existing studies explore how scientific linkages affect a firm's inventive productivity. For example, Aoki and Branstetter (2004) find a positive association between the intensity of patent citations related to academic science and subsequent research productivity at the firm level. Branstetter and Ogura (2005) support the idea that the main source of U.S. inventive activity has changed during the sample period, and comes with an increased emphasis on the use of the knowledge generated by university-based scientists. On the other hand, they find a positive relationship between a firm's inventive productivity and scientific linkages. Others who examine the relationship between scientific linkage and inventive productivity, such as Sorenson and Fleming (2004), Cassiman et al. (2008) and Nagaoka (2007), also find a positive relationship. These studies indicate that scientific linkage improves a firm's innovation productivity, implying that scientific linkage is likely to enhance a firm's productivity.

This paper uses patent data of electronics firms listed on the Taiwan Stock Exchange (TSE) which held at least one U.S. patent approved by the USPTO (United States Patent and Trademark Office) to evaluate the contribution of scientific linkages to total factor productivity (TFP) of the firm. Our data set includes a sample of 149 firms for the period 2004–2008. Taiwanese firms hold a very important position in the world market of semiconductors, computers and peripheral equipment, and electronic parts and components. Furthermore, the inventive activities of Taiwanese electronics firms are vigorous. According to the USPTO, the number of U.S. patents issued to firms in Taiwan ranked 4th in the world in 2008 (National Science Council, 2008).

Our firm-level scientific linkage is measured by the number of scientific publications cited by a firm's patents relative to the citations of other patents (i.e., intensity of citation of scientific publications). Before giving a precise definition of our measure of scientific linkage, we first explain the reference information of a patent. For a U.S.-approved patent, the references include citations of previous patents as well as non-patent references (NPRs, Narin et al., 1997). The former can be divided into U.S. patent citations and non-U.S. ones. The latter can be separated into several types, including scientific journal papers, conference proceedings, books, and many non-scientific citations such as industrial standards, technical disclosures, engineering manuals, and every other conceivable kind of published material (Narin et al., 1997).

In the literature, "scientific linkage" is measured in different ways. Nagaoka (2007) uses the CHI research scientific citation index. Branstetter and Ogura (2005) use the number of U.S. patent citations made to scientific articles generated by academic research in the state of California. Cassiman et al. (2008) use the scientific non-patent references (SNPR) cited by the focal patent and found in the Institute for Scientific Information (ISI) to measure the invention-specific scientific connection. By linking to ISI, they could single out the scientific articles in the NPRs. We utilize Cassiman et al.'s (2008) definition and Narin et al.'s (1997) classification to define scientific linkage, i.e., references of scientific publications found in the ISI (including journal articles, conference proceedings, books, and working papers).[3]

Our empirical analysis of the relationship between scientific publications and firms' productivity accounts for the possible endogeneity of scientific publications. Endogeneity of scientific citation has never been considered in previous studies. It is likely that there are unobserved factors affecting a firm's productivity, such as the firm's operating style and practices, R&D strategy, technical capa-

[1] Branstetter (2004) also suggests that there is an increasing trend in the science references cited by patents.

[2] Even though there exist different interpretations of backward citation of patents, there is no doubt that knowledge spillovers between firms are important. For example, by examining the relationship between a firm's productivity and other firms' patent applications (i.e., an indicator of their knowledge stock), Lee et al. (2015) find that knowledge spillovers from firms in the same business group are more significant than those from other firms. They also investigate the relative importance of inter- and intra-sector knowledge spillovers, and find that both are equally important.

[3] The university publications could include technical reports or working papers but not journal or conference papers generated by university-based scientists.

bility of employee, managers' ability. These factors can also affect the propensity for a firm to use other patents or scientific publications as references in its own R&D.[4] This generates an endogeneity problem. If endogeneity is not accounted for, the regression results will be biased. To account for endogeneity, we use a firm's liquidity constraints as instrumental variables.

After controlling for endogeneity of a patent's citations, we find that the intensity of citation of scientific publications has a large and positive impact on the patent-owning firm's total factor productivity.[5] This suggests that a patent using relatively more scientific discoveries directly from scientific publication contributes more its owner's productivity. Our findings have the important implication that bridging the gap between scientific discoveries and industrial technology would greatly enhance a country's productivity. However, currently the intensity of scientific citation is low. This is probably due to firms' lack of scientific knowledge to translate scientific discoveries into technology or their lack of information about scientific discoveries that could be used in developing useful technology. It is also possible that a firm does not have the funding to develop their technology using scientific discoveries directly. There is much that a government could do. For example, a platform could be created to facility collaborations between academic scientists and firms and funding could be provided for such collaborations.

The rest of the paper is organized as follows. In Section 2 we describe the pattern of R&D activities and scientific publications cited in patents owned by the TSE-listed electronics firms. In Section 3 we present our empirical strategy. The data and variables are described in Section 4. Our estimation results are reported and discussed in Section 5. We give some concluding remarks in Section 6.

2. Inventive scientific activity among Taiwanese electronics firms

Through continuous investment in R&D, the number of patents granted to firms in Taiwan has grown. Since 1978, Taiwanese firms have had an increasing number of patents approved by the USPTO. There were 7 patents granted in 1978 and over 100 were granted in 1989. The growth rate has been rising substantially. In 2007, the number of U.S. patents granted to Taiwanese firms reached 7493, with the country being ranked 4th by the USPTO (National Science Council, 2008) in terms of the number of patents granted.

Between 1978 and 2002, the most important areas of patented technologies granted to Taiwanese firms were as follows: semiconductor device manufacturing (24.9%), electrical connectors (8.12%), active solid-state physical devices (5.98%), electrical systems and devices (2.83%), static information storage and retrieval (2.24%), the processing, composition and production of radiation imagery chemistry (1.71%), computer graphics processing, interface processes and optical display systems (1.33%), multiple active non-linear electrical devices, and circuits and systems (1.13%). Most of these patents belong to the fields of electrical machinery and information technology. In terms of industry classification, most of Taiwan's U.S.-approved patents in 1978–2002 concentrated in the electronics and electrical machinery (54.81%), machinery (15.72%), scientific instruments (6.55%), and metal spare parts (5.55%). The rate of patent applications was much higher for the electronics and electrical machinery industry than for machinery. This shows that the electronics and electrical machinery industry is the most R&D-active one in Taiwan. The contribution of knowledge accumulated by firms in this industry and the relation of efforts spent engaging in innovation research to a firm's productivity are issues of concern in Taiwan.

There were 340 electronics firms listed on the TSE at the end of March 2009.[6] As of the end of December 2008, 222 of these 340 firms had obtained U.S.-approved patents. Table 1 reports the pattern of U.S.-approved patent ownership in different electronic sub-industries. The Computer and Peripheral industry had the highest ratio (89.29%) of firms having obtained U.S.-approved patents at least once. The second is the Optoelectronics industry (75%), which is followed by the Semiconductors & Communications and Internet industries (73.68% and 70.59%, respectively). The lowest were firms in the Electronic Products Distribution and Information Services industries (25% and 30%, respectively).

Firms holding U.S.-approved patents are divided into two groups, "firms with scientific linkages" and "firms without scientific linkages" based on the definition that non-patent references cited by a firm's patent found in the ISI. Observation of the two groups shows that the proportion of the firms with scientific linkages is not very large (see Table 2). Of the 222 firms with U.S.-approved patents, only 52 have patents that cite at least one ISI publications (i.e., 25.68%). At the sub-industry level, the highest number of firms holding patents where scientific ISI publications are cited is in the Semiconductors industry (48.78%). It is followed by the Information Services, and Communications & Internet industries (33.33% for both). Next are the Other Electronics (25.00%) and Optoelectronics (23.81%) industries. From this, we can see that the Semiconductor industry has the closest connection with scientific research in academia, followed by the Information Services, Electronic Product Distribution, Other Electronics, and Optoelectronics industries.

Next, we use the average number of ISI journal articles cited per patent as an indicator to show the trend of scientific publications cited in U.S.-approved patents held by electronics firms for the period from 2004 to 2008. An examination of Table 3 shows that, in 2004, the Information Service industry has the highest average (1.5), the second highest is the Semiconductors industry (0.0606). They are followed by the Communications & Internet and Optoelectronics industries (0.0282 and 0.0212, respectively).[7] In 2008, the Semiconductors industry has the highest average (0.4473). It is followed by the Communications & Internet and Optoelectronics industries. There was a conspicuous rise in the average number of citations of scientific publications by patents in the Semiconductors industry during 2004–2008. There was an increase in the ratio for Communications & Internet and Electronic Product Distribution industries during 2004–2007, but it dropped in 2008. The Optoelectronics, Electronics Parts/Components, Computers & Peripheral Equipment and Other Electronics industries showed no obvious changes. For the electronics industry as a whole, the average number of scientific publications cited in patents moved upward year by year.

3. Empirical strategy

We explore the effect of scientific linkage between patents and academic science on a firm's TFP. We account for the potential

[4] See Bloom et al. (2014) for a survey on the association between management practice and firm performance, and Lee et al. (2016) for empirical results based on firms in Japan and Korea.

[5] In our study, we utilize the method of Good et al. (1996) to measure total factor productivity (TFP). The results are robust when we use other measures.

[6] A complete list of listed firms in Taiwan can be obtained at the Market Observation Post System (http://emops.tse.com.tw/) of the TSE. The classification of electronics industries is the one used by the TSE on July 2, 2007.

[7] Because patents held by firms in the Information Service and Electronic Product Distribution industries are rare, we do not include these two industries in our empirical analysis.

Table 1
Number and percentage of Taiwan Stock Exchange-listed electronic firms with U.S.-approved patents.[a]

Industries	Number of firms with U.S.-approved patents (number of patents)	Percentage (%)	Number of firms without U.S.-approved patents	Percentage (%)	Total number of firms
Semiconductors	41 (13,933)	71.93	16	28.07	57
Optoelectronics	42 (2358)	75.00	14	25.00	56
Communications and Internet	24 (500)	70.59	10	29.41	34
Information Services	3 (17)	30.00	7	70.00	10
Electronic Products Distribution	6 (36)	25.00	18	75.00	24
Electronic Parts/Components	36 (1837)	52.17	33	47.83	69
Computers and Peripheral Equipment	50 (3169)	89.29	6	10.71	56
Other Electronics	20 (5547)	58.82	14	41.18	34
Total Electronics industries	222 (27,397)	65.29	118	34.71	340

[a] Companies holding at least one U.S.-approved patent as of Dec. 31, 2008. 340 electronics companies were listed on the TSE on March 31, 2009.

Table 2
Number and percentage of Taiwan Stock Exchange-listed electronics firms with patents referencing ISI papers.[a]

Industries	Number of firms with ISI papers	Percentage (%)	Number of firms without ISI papers	Percentage (%)	Total number firms with U.S.-approved patents
Semiconductors	20	48.78	21	51.22	41
Optoelectronics	10	23.81	32	76.19	42
Communications and Internet	6	25.00	18	75.00	24
Information Services	1	33.33	2	66.67	3
Electronic Products Distribution	2	33.33	4	66.67	6
Electronics Parts/Components	4	11.11	32	88.89	36
Computers and Peripheral Equipment	9	18.00	41	82.00	50
Other Electronics	5	25.00	15	75.00	20
Total electronics industries	57	25.68	165	74.32	222

[a] According to Table 1, the firms holding U.S.-approved patents can be divided into those with or without referencing scientific publications. The ISI papers are defined in Cassiman et al. (2008).

Table 3
Average number of ISI journal articles cited in U.S.-approved patents held by Taiwan Stock Exchange-listed electronics firms.

Industries	2004	2005	2006	2007	2008
Semiconductors	0.0606	0.1962	0.2529	0.2722	0.4473
Optoelectronics	0.0212	0.0167	0.0499	0.0436	0.0430
Communications and Internet	0.0282	0.0392	0.1176	0.4146	0.0543
Information Services	1.5000	0.0000	0.0000	0.0000	0.0000
Electronics Product Distribution	0.0000	0.1667	0.1429	0.6000	0.0000
Electronics Parts/Components	0.0150	0.0048	0.0171	0.0103	0.0048
Computers and Peripheral Equipment	0.0000	0.0165	0.0050	0.0139	0.0071
Other Electronics	0.0087	0.0024	0.0185	0.0181	0.0221
Total Electronics Industries	0.0337	0.0984	0.1241	0.1448	0.1779

Data Source: This paper.

endogeneity of scientific publications cited in the patents and number of patents obtained by a firm by using instrumental variables.

3.1. Total factor productivity function

Assume that the TFP function for any given firm can be written as follows:

$$\ln TFP_{it} = \beta_0 + \delta SCIENCE_{it} + \lambda PATENT_{it} + \beta X_{it} + \pi y_t + \mu_i + \varepsilon_{it} \quad (1)$$

where ln*TFP* is the total factor productivity, *SCIENCE* and *PATENT* are assumed to be endogenous, with *SCIENCE* indicating the ratio of the number of scientific publications to patents cited in a firm's patents (i.e., intensity of scientific citations), and *PATENT* is the number of patents owned by a firm. The vector *X* includes other control variables, i.e., ln(*ASSET*), the log of the firm's total assets, Ln(*SIZE*) and Ln(*SIZE*)^2, the log of the size of a firm and its square term, *AGE* and *AGE*^{2}, a firm's age and its square term, and sub-industry dummies. The variable y_t stands for time dummy for year *t*, μ is the firm fixed effect, and ε is a disturbance term. The parameters to be estimated are δ, λ, β and π. The subscripts *i* and *t* index firm and year, with, $i = 1, 2, \ldots, n$, $t = 2004, 2005, 2006, 2007, 2008$.

Younger and smaller firms are usually more productive because of their flatter organizational structure, which allows them to be more flexible in exploiting new opportunities and adapting to changes in the business environment (see the seminal work of Williamson, 1967; Dhawan, 2001, for empirical evidence). However, being smaller and younger also implies economies of scale and the benefits of learning-by-doing work against them, and they may have a lower initial stock of technological knowledge. This implies that firm size and age may have a nonlinear effect on productivity. The exact relationship between firm size/age and productivity would depend on the average scale/age of the sample firms and the industries that these firms belong to. To allow for a flexible functional form for firm age and size, we adopt a quadratic form for them. We proxy a firm's stock of capital by its total assets, which is expected to boost a firm's productivity.

Industry dummies are included to control for things such as omitted inputs, differences in average degree of vertical integration, and the average level of technological knowledge (see Hall, 2011). Firm fixed effects are included to control for unobserved time-invariant heterogeneity. Year fixed effects are included to control for year specific macroeconomic shocks. The specification of model (1) largely follows that in the literature (see Hall, 2011; for a review).

We use the vector distance index (developed by Good et al., 1996) between output and input to measure a firm's total factor productivity, according to which the TFP with a single output is:

$$\ln TFP_{it} = (\ln Y_{it} - \ln \bar{Y}_t) + \sum_{s=2}^{t} (\ln \bar{Y}_s - \ln \bar{Y}_{s-1})$$
$$- \left[\frac{1}{2} \sum_{k=1}^{K} (\alpha_{kit} + \overline{\alpha_{kt}})(\ln X_{kit} - \overline{\ln X_{kt}}) + \sum_{s=2}^{t} \frac{1}{2} \sum_{k=1}^{K} (\overline{\alpha_{ks}} + \overline{\alpha_{k,s-1}})(\overline{\ln X_{ks}} - \overline{\ln X_{k,s-1}}) \right], \quad (2)$$

where Y is output, X is factor input, and $\alpha$is cost share. Subscript i indexes firm, $i = 1, 2, \ldots, n$; k indexes factor input, $k = 1, 2, \ldots, K$, which includes capital and number of employees; s indexes year, $s = 1, 2, \ldots, t$, $\overline{\ln Y}$, $\overline{\ln X}$ and $\overline{\ln \alpha}$ are the geometric averages of output, factor input and cost share, respectively.

The intensity of scientific citations *SCIENCE* represents the scientific linkage of a firm's technology. We have two different measures of scientific citations following Cassiman et al. (2008) and Narin et al. (1997). The narrowest one, denoted by *SCIENCE-ISI*, is defined as the ratio of the number of citations of ISI journal articles (i.e., papers published in journals indexed by the Web of Science) to that of other patents. The second measure, which is looser than the first one, is defined as ratio of citations of all scientific publications (including ISI journal articles, conference papers, books, and working papers) to citations of other patents. It is denoted by *SCIENCE-ALL*. The intensity of scientific references *SCIENCE* and number of patents *PATENT* may be endogenous. Endogeneity arises from the existence of unobservable factors that affect both a firm's productivity and its innovative behavior. For example, a firm having employees or major shareholders with better technological knowledge or capability would be more productive and more likely to use discoveries from scientific publications directly in their R&D. To account for these unobserved factors affecting productivity and references used in their R&D, we use the instrumental variable approach.

3.2. Instrumental variable estimation method

To use the instrumental variable approach, we first set up reduced form models for the endogenous variables *SCIENCE* and *PATENT*, respectively.

$$SCIENCE_{it} = \gamma_0 + \gamma Z_{it} + \eta X_{it} + \kappa_i + u_{it}, \quad (3)$$

$$PATENT_{it} = \theta_0 + \theta Z_{it} + \rho X_{it} + \xi_i + v_{it}, \quad (4)$$

where Z is a vector of instruments consisting of three measures of a firm's financial constraints (i.e., the *t-1* to *t-6* averages of cash flow, denoted by *CASH*, long-term loan, denoted by *LOAN*, and interest payments, denoted by *INTEREST*), and γ, η, θ *and* ρ are parameters to be estimated, and κ_i and ξ_i are firm fixed effects. Endogeneity implies that there is a correlation between ε_{it} and u_{it}, and between ε_{it} and v_{it}. These reduced form models are needed whether we are using the two-stage least squares or other estimators with instrumental variables for estimation. The reduced form models also enable us to check whether the basic assumptions are satisfied when using instrumental variables.

We use measures of a firm's financial constraints as instrumental variables to identify the causal effect of scientific citation intensity and number of patents on its productivity. For a variable to be a valid instrument, it must have enough explanatory power toward the endogenous regressors, but unrelated to unobserved factors affecting the outcome variable of interest. Measures of a firm's financial constraints seem to meet these requirements.

The sensitivity of R&D investment to financial constraints is likely to be due to asymmetric information between a firm and its creditors (Gorodnichenko and Schnitzer, 2013). There is a large literature on the effect of financial constraints and innovation (see, e.g., Myers and Majluf, 1984; Fazzari et al., 1988; Hall, 1992; Himmelberg and Petersen, 1994; Bhagat and Welch, 1995; Ryan and Wiggins, 2002; Trushin, 2011). The findings obtained in these studies suggest that financial constraints hamper investment in R&D projects and innovation. Himmelberg and Petersen (1994) find a very significant relationship between R&D investment and financial constraints among small firms in France. Hall's (1992) findings suggest that there is a positive relationship between R&D investment and cash flow. Ryan and Wiggins (2002) find that the ability to finance projects with internal sources alleviates the underinvestment problem where information asymmetries related to assets could lead managers to reject positive NPV (Net Present Value) projects (Myers and Majluf, 1984). Trushin (2011) find that a 10% growth in cash flow leads to a 3.6% growth in R&D expenditures. These results suggest that companies with higher cash flow are also more likely to spend more on R&D.

Himmelberg and Petersen (1994) show that the major source of R&D investment financing is internal not external. There may be a possibility of a high payoff but also a high risk with an R&D project and these projects may increase the risk of bankruptcy. But if the project is successful, the lender cannot obtain the profits. Hence, most creditors do not have incentive to provide funding for R&D projects. Bhagat and Welch (1995) suggest that since R&D investment yields future benefits that are less likely to be realized if the firm becomes distressed, firms with high financial leveraging would spend less on R&D projects (Ryan and Wiggins, 2002).

Intuition suggests that financial constraints are unlikely to be related to unobserved factors affecting both a firm's productivity and its patents' citation of scientific publications (e.g., technical knowledge/capability of employee or major shareholders). Findings of previous studies also imply that financial constraints do not have a direct effect on a firm's productivity. For example, the asymmetric information between a firm and its external creditors are less serious for investment in physical capital, especially for larger firms, such as those in our sample. This implies that physical capital investment (which affects a firm's productivity) is not affected by finance constraints. This is supported by Brown and Petersen's (2009) findings that U.S. firms' R&D is sensitive to cash flow, but their physical capital investment is not. This implies that firms facing financial constraints will engage in less risky and shorter term R&D projects, e.g., projects building on previous patents' technology instead of translating discoveries from scientific publications.

Moreover, Li (2011) find that the connection between financial constraints and stock returns is large and statistically significant for high R&D intensive firms but small and statistically insignificant for low R&D intensive firms. These findings indicate that R&D investment is sensitive to financial constraints and the relationship between financial constraints and a firm's stock returns (which is related to its productivity and profitability) is likely to be driven by the R&D-financial constraints relationship. Thus, Li's (2011) findings also support our argument that financial constraints do not have a direct effect on a firm's performance.

We use lagged measures (the averages of years *t-1* to *t-6*) of financial constraints as instruments. This is to take into account the fact that it usually takes a few years for a patent's technologies to be developed and for the patent to be granted after an application is filed. The average number of years it takes for a patent application to be approved varies, depending on the technologies

Table 4
The number of firms in sample.

Industries	Number of firms	(%)
Semiconductors	35	23.49
Optoelectronics	31	20.81
Communications and Internet	13	8.72
Electronic Parts/Components	21	14.09
Computers and Peripheral Equipment	36	24.16
Other Electronics	13	8.72
Total Electronics Industries	149	100

Table 5
Backward citation of sample firms' patents.

Types of reference sources	(1) Citation per Patent	(2) Total Number of Citations	(3) Ratio of scientific/patent citations
ISI Journals	0.0381	2.62	0.0056
All Scientific Publications	0.1032	6.99	0.0148
Patents	6.2640	179.18	

Table 6
Descriptive statistics.

Variable	Definition	Mean (Std. Dev.)
ln*TFP*	The total factor productivity of a given firm	0.0659 (1.0080)
SCIENCE-ISI	Intensity of scientific citation of a firm's patents: $\frac{\text{citation of ISI–Journal Articles}}{\text{citation of other patents}}$.	0.0057 (0.0217)
SCIENCE-ALL	Intensity of scientific citation of a firm's patents: $\frac{\text{citation of all scientific publications}}{\text{citation of other patents}}$, where scientific publications include ISI-journal articles, conference papers, working papers, and books	0.0148 (0.0424)
PATENT	The number of patents owned by a given firm	25.7949 (69.8171)
ln(*ASSET*)	The total assets of a given firm (NTD)[a]	16.2947 (1.5236)
ln(*SIZE*)	The number of employees of a given firm	6.8269 (1.2428)
ln$(SIZE)^2$	The square term of ln(*SIZE*)	48.1482 (17.7556)
AGE	The age of a given firm	20.0752 (9.1984)
AGE^2	The square term of *AGE*	487.4803 (482.6688)
CASH	The average of lags 1–6 years for the cash flow from operations of a given firm (billions of NTD)[a]	0.0379 (0.1371)
LOAN	The average of lags 1–6 years for the long-term loans of a given firm (billions of NTD)[a]	0.0322 (0.1265)
INTEREST	The average of lags 1–6 years for the interest payments of a given firm (billions of NTD)[a]	0.0164 (0.0974)
Observations		585

[a] Measured in 2004 constant TWD.

involved. It usually takes about 2–3 years for an application to be approved. For the firms in our sample, which were all listed on the TSE, it took an average of 2.03 years for a patent to be approved.[8] In addition to the time lag between application and approval of a patent, before a firm files a patent application, it takes time for the firm to develop the technology for the patent. The difference in the timing of the instruments and our outcome variable (i.e., productivity) also implies that there is unlikely to be a correlation between them.

4. Data sources and variables

We use data for TSE-listed electronics firms that have obtained at least one U.S.-approved patent. Our sample includes 149 firms with 585 observations for the period 2004–2008.[9] These firms belong to the following six sub-industries: Semiconductors, Optoelectronics, Communications and Internet, Electronic Parts/Components, Computers and Peripheral Equipment and Other Electronics. Among them, there are fewer firms which have U.S.-approved patents in the Information Services and Electronic Products Distribution industries (Information Services has three and Electronic Products Distribution has six firms with U.S.-approved patents). Therefore, we do not include firms in these two industries in our sample. The number of observations for each industry is listed in Table 4. The Computers and Peripheral Equipment group has the highest percentage (24.16%), which is followed by Semiconductors (23.49%) and Optoelectronics (20.81%). These firms' patent data were obtained from the Delphion intellectual property network's patent search database (www.delphion.com). We use a firm's name in English as the keyword to search for information on its U.S.-approved patents. A firm's characteristics (cash flow from operations; long-term loans and interest payments; total assets; R&D expenditure; number of employees and firm age) were obtained from the Taiwan Economic Journal database.

[8] The average year is calculated from U.S.-approved patents in the period from the date of the first U.S.-approved patent obtained by the firm to December 31, 2008.

[9] Since the three companies Chungwha Telecom, Senao International and Far EasTone Telecommunications in the Communications and Internet industry are service-oriented companies, we did not use them in our empirical analysis. In addition, we delete 4 observations whose average sum of ISI-papers and conference proceedings cited by a patent were bigger than 3, i.e., outliers. After deleting these observations, there are 585 observations in our sample.

Table 5 exhibits some descriptive statistics of citations in patents owned by firms in our sample. These patents use far more patents than scientific publications as references. On average, a patent cites 6.3 other patents, but only 0.03 ISI journal articles or 0.1 scientific publications. On average, a firm cites 2.62 ISI journal articles, 7 scientific publications and 179.2 patents in its patents.

We define two different measures of scientific references (relative to referencing of other patents). The first adopts the narrowest definition, namely the citation of articles published in ISI journals relative to citation of patents, denoted *SCIENCE-ISI*. Articles published in ISI-journals meet certain standard and make at least some academic contributions. It is likely that patents citing more articles in ISI-journals contribute more to a firm's productivity. The second measure is *SCIENCE-ALL* (i.e., citations of ISI-journal articles and non-journal publications, e.g., conference proceedings or papers, working papers, or books) relative to citation of patents. This measure of scientific linkage is a very loosely defined one. Descriptive statistics of variables used in our empirical analysis are reported in Table 6.

Table 7 exhibits the correlation matrix among the key variable in our empirical work. The Table shows that the correlation between any two explanatory variables are not particularly high such that multi-collinearity is not a problem.

5. Empirical results

Table 8 reports the estimation results for the reduced models (3) and (4). The *F*-Statistics are 6.6412 and 7.3185, respectively, for *SCIENCE-ISI* and *SCIENCE-All*. This suggests that the instruments have reasonable explanatory power for the two endogenous regressors. However, they are not very strong, since they are below the critical value of 9.08 suggested by Stock and Yogo (2005). Because of this, we use the limited information maximum likelihood (LIML) estimator, which is robust to weak instruments. It is shown that the LIML estimator's asymptotic distribution has a median which is closer to the true parameter if the instruments are weak (see Staiger and Stock, 1997).

The coefficient estimates of *CASH* are positive and significant for both measures of scientific citation intensity (see columns (1) and (2) of Table 8). The positive coefficient of lag cash flow suggests that a firm with a higher level of cash flow in previous years cites more scientific references in their own patents. This result is consistent with the past studies by Hall (1992), Ryan and Wiggins (2002), and Trushin (2011). Specifically, having a coefficient of 0.0411 and 0.1007 on the scientific reference intensity measures *SCIENCE-ISI* and *SCIENCE-ALL* implies that a one billion increase in cash flow leads to a 0.0411–0.1007 unit increase in the scientific-patent citation ratio. The coefficient estimate of the effect of *CASH* on the citation of patents is negative, but it is statistically insignificant.

The coefficient estimates of *LOAN* for the two measures of intensity of scientific reference are −0.0027 and −0.0058 suggesting a firm with more outstanding loans is less likely to use discoveries directly from scientific publications.[10] This result is also in line with previous empirical findings (e.g., Ryan and Wiggins, 2002, and Trushin, 2011). It is also found that the instrumental variable *INTEREST* has a negative and statistically significant effect on the two measures of the intensity of scientific references. The coefficient estimates, −0.0071 and −0.0164, suggest that if a firm has a heavier interest payment burden, it will cite less scientific publications in their patents. The financial constraints variables have similar effects on the number of patents that a firm has, except

Table 7
Correlation matrix.

	lnTFP	PATENT	SCIENCE-ISI	SCIENCE-ALL	ln(ASSET)	ln(SIZE)	AGE	CASH	LOAN	INTEREST
lnTFP	1.0000									
PATENT	0.2004 [0.0000]*	1.0000								
SCIENCE-ISI	−0.0504 [0.2240]	0.1185 [0.0041]	1.0000							
SCIENCE-ALL	−0.0274 [0.5080]	0.1629 [0.0001]	0.7489 [0.0000]	1.0000						
ln(ASSET)	0.4148 [0.0000]	0.4979 [0.0000]	0.0902 [0.0292]	0.1347 [0.0011]	1.0000					
ln(SIZE)	0.0514 [0.2146]	0.4122 [0.0000]	0.0810 [0.0503]	0.1329 [0.0013]	0.8670 [0.0000]	1.0000				
AGE	−0.1431 [0.0005]	0.0895 [0.0305]	−0.0636 [0.1241]	−0.0731 [0.0775]	0.0659 [0.1113]	0.0890 [0.0313]	1.0000			
CASH	0.0229 [0.5805]	0.6146 [0.0000]	0.1652 [0.0001]	0.2222 [0.0000]	0.4833 [0.0000]	0.4714 [0.0000]	−0.0157 [0.7048]	1.0000		
LOAN	−0.0310 [0.4541]	0.1243 [0.0026]	0.0221 [0.5942]	0.0399 [0.3356]	0.4265 [0.0000]	0.4442 [0.0000]	−0.0455 [0.2716]	0.3204 [0.0000]	1.0000	
INTEREST	−0.0555 [0.1797]	0.0507 [0.2205]	0.0069 [0.8680]	0.0228 [0.5826]	0.2369 [0.0000]	0.2180 [0.0000]	−0.0124 [0.7649]	0.1833 [0.0000]	0.1411 [0.0006]	1.0000

* *p*-value in square brackets.

[10] These estimates are not statistically significant though.

Table 8
Reduced-form models estimation results.[a]

	(1) *SCIENCE-ISI*	(2) *SCIENCE-ALL*	(3) *PATENT*
Ln(*ASSET*)	0.0030	−0.0011	2.5249
	(0.0033)	(0.0081)	(4.3603)
Ln(*SIZE*)	0.0078	0.0420	−46.6783
	(0.0177)	(0.0269)	(29.4253)
Ln(*SIZE*)^2	−0.0010	−0.0034	4.2369
	(0.0015)	(0.0023)	(2.5941)
AGE	0.0006	0.0026	0.8669
	(0.0011)	(0.0024)	(1.6607)
AGE^2	−0.0000	−0.0000	0.0080
	(0.0000)	(0.0000)	(0.0345)
*YEAR*2004	0.0035	−0.0021	−59.8013***
	(0.0079)	(0.0157)	(14.6617)
*YEAR*2005	0.0045	0.0062	−51.1806***
	(0.0067)	(0.0148)	(12.3477)
*YEAR*2006	0.0072	0.0077	−30.8328***
	(0.0056)	(0.0101)	(7.7006)
*YEAR*2007	0.0037	0.0043	−17.8013***
	(0.0044)	(0.0079)	(4.6167)
CASH	0.0411***	0.1007***	−53.9604
	(0.0121)	(0.0330)	(58.1239)
LOAN	−0.0027	−0.0058	54.3149
	(0.0069)	(0.0160)	(51.6382)
INTEREST	−0.0071**	−0.0164*	−36.6469***
	(0.0031)	(0.0094)	(13.0049)
Observations	585	585	585
R^2	0.028	0.026	0.112
Fixed Effects	Yes	Yes	Yes

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
[a] Standard errors, clustered at the firm level, in parentheses.

that only *INTEREST* has a statistically significant (negative) effect on *PATENT*.

Columns (3) and (4) of Table 9 report the LIML estimation results for the casual effect of the intensity of scientific citation on productivity (i.e., estimation of model (1) with instruments). The *p*-value of the χ^2-statistic of the over-identification restriction test is between 0.0588 and 0.0475, implying that the *p*-value is far above 0.05. Thus, we accept the null hypothesis that the instruments are exogenous for the two measures of scientific citations.[11]

Table 9's results indicate that both *SCIENCE-ISI* and *SCIENCE-ALL* have a positive and statistically significant effect on a firm's TFP. The measure *SCIENCE-ISI* has a larger coefficient estimate, with the magnitude being 22.5648 (see column (3) of Table 9). This implies that doubling the science-patent citation ratio from 0.0057 (the sample average) to 0.0114 will increases productivity by 13.73%.[12] The looser measure *SCIENCE-ALL* has a much smaller effect. With its coefficient estimate being 8.9330, doubling the scientific citation intensity from 0.0126 (sample average) to 0.0252 will increase a firm's productivity by 11.91%. The greater effect of citing ISI journal articles is likely to be due to the fact that articles published in the ISI journals are more rigorous than books or non-journal publications. Also, it usually takes longer for an author to write a book than a journal article, such that findings in journal articles are more relevant than those in books.

The estimates of the effect of the number of patents owned by a firm on the firm's productivity is statistically insignificant. This is very different from findings obtained by previous studies (e.g., Hall, 2011). The difference may arise from the fact that previous studies do not account for endogeneity of the number of patents

Table 9
LIML estimation results—effects of citation of scientific publications.[a]

	OLS		LIML	
	(1)	(2)	(3)	(4)
SCIENCE-ISI	1.1248		22.5648**	
	(0.7082)		(9.7565)	
SCIENCE-ALL		0.8292*		8.9330**
		(0.4676)		(4.0531)
PATENT	0.0016**	0.0016**	0.0013	0.0013
	(0.0008)	(0.0007)	(0.0048)	(0.0052)
Ln(*ASSET*)	0.8029***	0.8068***	0.7318***	0.8091***
	(0.1292)	(0.1286)	(0.1562)	(0.1430)
Ln(*SIZE*)	−0.3949	−0.4128	−0.3856	−0.5901
	(0.4628)	(0.4642)	(0.6803)	(0.6190)
Ln(*SIZE*)^2	−0.0255	−0.0246	−0.0180	−0.0106
	(0.0317)	(0.0318)	(0.0514)	(0.0469)
AGE	−0.0042	−0.0061	−0.0269	−0.0364
	(0.0369)	(0.0372)	(0.0496)	(0.0501)
AGE^2	−0.0002	−0.0002	0.0000	0.0002
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
*YEAR*2004	−1.9672***	−1.9582***	−1.9787***	−1.8835***
	(0.1735)	(0.1729)	(0.3974)	(0.4098)
*YEAR*2005	−1.4225***	−1.4199***	−1.4701***	−1.4264***
	(0.1367)	(0.1355)	(0.3170)	(0.3288)
*YEAR*2006	−0.9574***	−0.9538***	−1.0763***	−0.9835***
	(0.0886)	(0.0877)	(0.1993)	(0.1984)
*YEAR*2007	−0.4531***	−0.4515***	−0.5140***	−0.4698***
	(0.0479)	(0.0475)	(0.1257)	(0.1191)
Over-identification test			1.1185	1.1285
			[0.2902]	[0.2881]
Endogeneity test			2.1458	2.0457
			[0.1430]	[0.1526]
Observations	585	585	585	585
R^2	0.328	0.333	−1.139	−0.463
F-statistic			6.6412	7.3185
Fixed Effects	Yes	Yes	Yes	Yes

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
[a] *p*-values in square brackets and firm-level clustered standard errors in parentheses.

that a firm owns. As can be observed in columns (1) and (2) in Table 9, when model (1) is estimated with OLS and endogeneity is not accounted for, the number of patents owned by a firm has a positive and significant effect on its productivity.

We use the Durbin-Wu-Hausman test to check whether the intensity of scientific citation measures is endogenous. As reported in columns (3) and (4) of Table 9, the *p*-value of the Durbin-Wu-Hausman test statistics for both measures of scientific citations intensity are larger than 0.05. This suggests that the null hypothesis of exogeneity cannot be rejected even though the differences between the OLS and IV estimates are large. The acceptance of the null of exogeneity is probably because the standard errors of the fixed effects estimates are large and these OLS estimates are either statistically insignificant or only marginally significant. The large standard errors of the OLS estimates cause the variance of the test statistics to be too large for us to draw a definite conclusion.

The coefficient estimates for other variables have the expected signs, especially those which are statistically significant at conventional levels. For example, the value of fixed asset, which is a measure of capital input, has a positive effect on productivity. While the age is statistically insignificant, its square has a negative coefficient, which is statistically significant at the 5% level, implying that older firms are less productive.

To check the robustness of our results with respect to our measures of productivity, we estimate model (1) again using different measures of a firm's productivity. Two alternative measures of productivity were experimented. The first is the TFP index used by Todo and Shimizutani (2008). This index is also based on Good et al. (1996), but it is computed using a firm's value added instead of

[11] The R^2 for the LIML regressions in Table 9 is negative. This happens because the residual of the regression model includes an additional error term from the reduced form regression models. This creates the possibility that the sum of squares of the residual is larger than the total sum of square of the dependent variable. See Wooldridge (2012, page 471).

[12] That is, 13.73 = (exp(22.5648 × 0.0057) − 1) × 100.

output. The second alternative measure of productivity is simply the output per employee *Y/L* as used by Hall (2011). The results are reported in Tables A1 and A2. While the instrumental variable estimates of the effect of scientific citation intensity is smaller in magnitude for labor productivity (see Table A2), about half of the estimates in Table 9, the estimates are similar in magnitude for the value added-based TFP (see Table A1).

To see whether the estimation results are sensitive to our measure of scientific linkage, we use (a) the scientific citations as a proportion of all types of citations (both patents and scientific publications) and (b) number of scientific citations as indicators of scientific linkages. The results are reported in Tables A3 and A4 in the Appendix. The results in Tables A3 and A4 are consistent with our baseline results in Table 9.

6. Conclusion

Innovation is a major driver of economic growth and can increase the value added and competitiveness of an economy and its firms. Over the past 20 years, R&D expenditure and research investment have increased rapidly all over the world. Also, there was a dramatic increase in the number of patents approved. An invention usually benefits from knowledge spillovers from academic research and other inventions, as indicated by a patent's citation of scientific publications or other patents. Increasingly, scientific publications are being cited in firms' patents (e.g., Narin et al., 1997 and Branstetter and Ogura, 2005). This implies that the knowledge spillover from academia to industry has become greater. Our study explores the contribution of this kind of scientific linkage to a firm's productivity.

We use a panel of listed electronics firms in the TSE for the period 2004–2008 to analyze the relationship between citations of scientific publications in a firm's patents on its productivity. We use instrumental variables to account for the potential endogeneity of the intensity of scientific citation of a firms' patents. Measures of a firm's financial constraints are used as instruments, namely, cash flow, value of long term loans and interest payments in the past six years.

Our estimation results suggest that the instruments have reasonable explanatory power toward the endogenous variables. Our empirical results suggest that a higher intensity of citation to scientific publications leads to a higher level of productivity. More specifically, doubling the current level of scientific citation intensity of firms in our sample would increase the average productivity by 13.73–11.91%. These findings suggest that knowledge from scientific publications is valuable in firm's innovative activity and productivity. However, the translation of scientific discoveries to technology may not be easy and firms may not have the necessary scientific knowledge or funding for the translation. This explains why the current intensity of citation of scientific publications is low. This implies that there is room for government interventions. For example, ear-marked funding (in the form of loans or equity investment) could be provided for academic scientists to transform their discoveries to applications. Moreover, a platform could be created to mediate the supply of scientific knowledge from academia and the demand by private firms. Finally, public or private institutions could be set up to provide financial resources and technical assistance to firms or academic laboratories to facilitate the translation of scientific discoveries to technological innovations.

The absorptive capability of a firm is another implication related to our results. Firms need to conduct R&D, a firm's R&D capability enables it to catch up with the development of scientific research in academic institutes. This makes it possible for firms to benefit from fundamental scientific discoveries.

Moreover, given that academic scientific research generates spillovers, the public benefits of academic scientific research should be taken into consideration when the government allocates funding for academic research. Also, when evaluating academic research output, these spillovers should be an important performance indicator.

Even though our empirical analysis is based on the case of Taiwan's electronic industry, which is dynamic and innovative, to a large extent the findings are useful for other industries and countries. The implications of our results and policy suggestions that we make based on these results still hold for industries where innovations are not reflected in the number of patents, e.g., the consumer product industries, or countries where the technological or scientific capability is not so advanced. For any country, no matter whether its industries are technologically advanced or not, academic scientific research and industrial R&D should be encouraged (by providing financial or technical assistance), and a platform mediating the supply and demand for scientific knowledge would benefit productivity.

Appendix A.

Tables A1–A4.

Table A1
LIML estimation results using value added-based TFP to measure productivity.[a]

	OLS		LIML	
	(1)	(2)	(3)	(4)
SCIENCE-ISI	1.1729		26.8725**	
	(0.8459)		(9.0731)	
SCIENCE-ALL		0.8082*		10.9174***
		(0.4838)		(3.1751)
PATENT	0.0033***	0.0033***	0.0064	0.0064
	(0.0012)	(0.0012)	(0.0044)	(0.0042)
Ln(*ASSET*)	0.7932***	0.7973***	0.6994***	0.7914***
	(0.1911)	(0.1907)	(0.2133)	(0.2031)
Ln(*SIZE*)	−0.0751	−0.0924	0.1186	−0.1287
	(0.7015)	(0.7043)	(0.8858)	(0.8400)
Ln(*SIZE*)^2	−0.0665	−0.0656	−0.0738	−0.0647
	(0.0506)	(0.0507)	(0.0678)	(0.0635)
AGE	0.0540	0.0522	0.0250	0.0126
	(0.0399)	(0.0401)	(0.0543)	(0.0525)
AGE^2	−0.0018**	−0.0018**	−0.0016*	−0.0014
	(0.0008)	(0.0008)	(0.0009)	(0.0010)
*YEAR*2004	−1.8047***	−1.7957***	−1.6131***	−1.4945***
	(0.2195)	(0.2192)	(0.4188)	(0.3888)
*YEAR*2005	−1.3245***	−1.3217***	−1.2044***	−1.1503***
	(0.1739)	(0.1728)	(0.3341)	(0.3148)
*YEAR*2006	−0.9187***	−0.9147***	−0.9552***	−0.8443***
	(0.1206)	(0.1199)	(0.2242)	(0.1983)
*YEAR*2007	−0.4591***	−0.4573***	−0.4712***	−0.4184***
	(0.0607)	(0.0602)	(0.1440)	(0.1217)
Over-identification test	0.0000	0.0000	0.2069	0. 3263
			[0.6492]	[0.5678]
Endogeneity test			1.9457	1.9500
			[0.1631]	[0.1626]
Observations	585	585	585	585
R^2	0.283	0.285	−1.055	−0.507
F-statistic			6.6412	7.3185
Fixed Effects	Yes	Yes	Yes	Yes

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
[a] *p*-values in square brackets and firm-level clustered standard errors in parentheses.

Table A2
LIML estimation results using Ln(Y/L) to measure productivity.[a]

	OLS		LIML	
	(1)	(2)	(3)	(4)
SCIENCE-ISI	0.8137		13.4629**	
	(0.5582)		(5.5983)	
SCIENCE-ALL		0.7561*		5.4771***
		(0.3999)		(1.9727)
PATENT	0.0011*	0.0010*	0.0039	0.0039
	(0.0006)	(0.0006)	(0.0031)	(0.0028)
Ln(*ASSET*)	0.9189***	0.9218***	0.8694***	0.9155***
	(0.1152)	(0.1146)	(0.1241)	(0.1171)
Ln(*SIZE*)	−0.6582	−0.6750	−0.4943	−0.6186
	(0.4400)	(0.4415)	(0.5342)	(0.5090)
Ln(*SIZE*)^2	−0.0179	−0.0169	−0.0276	−0.0230
	(0.0297)	(0.0297)	(0.0389)	(0.0366)
AGE	0.0110	0.0090	−0.0039	−0.0101
	(0.0318)	(0.0320)	(0.0384)	(0.0376)
AGE^2	−0.0002	−0.0002	−0.0001	−0.0000
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
YEAR2004	−1.3372***	−1.3296***	−1.1657***	−1.1064***
	(0.1483)	(0.1471)	(0.2856)	(0.2701)
YEAR2005	−0.9596***	−0.9582***	−0.8339***	−0.8070***
	(0.1157)	(0.1142)	(0.2308)	(0.2173)
YEAR2006	−0.6704***	−0.6686***	−0.6485***	−0.5931***
	(0.0747)	(0.0734)	(0.1498)	(0.1336)
YEAR2007	−0.3313***	−0.3306***	−0.3144***	−0.2880***
	(0.0410)	(0.0404)	(0.0912)	(0.0794)
Over-identification test	0.0000	0.0000	0.0588	0.0475
			(0.8084)	(0.8275)
Endogeneity test			1.5671	1.5449
			[0.2106]	[0.2139]
Observations	585	585	585	585
R-squared	0.440	0.445	−0.098	0.149
F-statistic			6.6412	7.3185
Fixed Effects	Yes	Yes	Yes	Yes

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
[a] *p*-values in square brackets and firm-level clustered standard errors in parentheses.

Table A3
Effects of citation of scientific publications—alternative measure of intensity of scientific citation.[a]

	OLS		LIML	
	(1)	(2)	(3)	(4)
SCIENCE-ISI#	1.2020		23.9536**	
	(0.7730)		(10.5313)	
SCIENCE-ALL#		0.9169*		10.4120**
		(0.5255)		(5.0121)
PATENT	0.0016**	0.0016**	0.0011	0.0007
	(0.0008)	(0.0008)	(0.0048)	(0.0053)
Ln(*ASSET*)	0.8025***	0.8069***	0.7254***	0.8111***
	(0.1293)	(0.1286)	(0.1575)	(0.1439)
Ln(*SIZE*)	−0.3923	−0.4089	−0.3459	−0.5842
	(0.4630)	(0.4643)	(0.6851)	(0.6278)
Ln(*SIZE*)^2	−0.0258	−0.0250	−0.0216	−0.0119
	(0.0317)	(0.0318)	(0.0512)	(0.0475)
AGE	−0.0434	−0.0451	−0.0165	−0.0462
	(0.0418)	(0.0417)	(0.0723)	(0.0654)
AGE^2	−0.0002	−0.0002	0.0000	0.0002
	(0.0009)	(0.0009)	(0.0010)	(0.0011)
YEAR2004	−1.9664***	−1.9561***	−1.9746***	−1.8859***
	(0.1735)	(0.1733)	(0.3981)	(0.4200)
YEAR2005	−1.4218***	−1.4180***	−1.4675***	−1.4312***
	(0.1367)	(0.1358)	(0.3167)	(0.3359)
YEAR2006	−0.9570***	−0.9526***	−1.0730***	−0.9873***
	(0.0886)	(0.0878)	(0.1987)	(0.2021)
YEAR2007	−0.4524***	−0.4500***	−0.5032***	−0.4632***
	(0.0479)	(0.0474)	(0.1224)	(0.1206)
Over-identification test	0.0000	0.0000	0.0588	0.0475
			(0.8084)	(0.8275)

Table A3 (*Continued*)

	OLS		LIML	
	(1)	(2)	(3)	(4)
Endogeneity test			1.5671	1.5449
			[0.2106]	[0.2139]
Observations	585	585	585	585
R-squared	0.328	0.332	−1.068	−0.470
F-statistic			6.2218	5.6244
Fixed Effects	Yes	Yes	Yes	Yes

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
#Proportion of references which are scientific publications.
[a] *p*-values in square brackets and firm-level clustered standard errors in parentheses.

Table A4
Effects of citation of scientific publications—citations in level.

	OLS		LIML	
	(1)	(2)	(3)	(4)
SCIENCE-ISI#	0.0029*		0.0127***	
	(0.0017)		(0.0049)	
SCIENCE-ALL#		0.0015**		0.0047***
		(0.0007)		(0.0017)
PATENT	0.0015**	0.0015**	0.0138*	0.0138*
	(0.0007)	(0.0007)	(0.0075)	(0.0074)
Ln(*ASSET*)	0.8137***	0.8152***	0.8007***	0.7979***
	(0.1285)	(0.1285)	(0.1857)	(0.1853)
Ln(*SIZE*)	−0.3686	−0.3626	0.6154	0.5917
	(0.4608)	(0.4598)	(0.8599)	(0.8503)
Ln(*SIZE*)^2	−0.0285	−0.0290	−0.1295*	−0.1270*
	(0.0316)	(0.0315)	(0.0669)	(0.0659)
AGE	−0.0437	−0.0426	0.0291	0.0321
	(0.0417)	(0.0416)	(0.0593)	(0.0571)
AGE^2	−0.0002	−0.0002	−0.0019**	−0.0019**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
YEAR2004	−1.9432***	−1.9369***	−1.5367***	−1.5540***
	(0.1753)	(0.1750)	(0.4538)	(0.4433)
YEAR2005	−1.4052***	−1.4002***	−1.0674***	−1.0785***
	(0.1385)	(0.1382)	(0.3765)	(0.3686)
YEAR2006	−0.9442***	−0.9427***	−0.7461***	−0.7550***
	(0.0892)	(0.0887)	(0.2281)	(0.2226)
YEAR2007	−0.4487***	−0.4487***	−0.3416***	−0.3464***
	(0.0476)	(0.0473)	(0.1270)	(0.1238)
Over-identification test	0.0000	0.0000	0.0588	0.0475
			(0.8084)	(0.8275)
Endogeneity test			1.5671	1.5449
			[0.2106]	[0.2139]
Observations	585	585	585	585
R-squared	0.330	0.333	0.022	0.045
F-statistic			3.5341	3.4238
Fixed Effects	Yes	Yes	Yes	Yes

†*p*-values in square brackets and firm-level clustered standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. #Number of scientific citations.

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Please cite this article in press as: Chen, J.-R., et al., Scientific linkages and firm productivity: Panel data evidence from Taiwanese electronics firms. Res. Policy (2016), http://dx.doi.org/10.1016/j.respol.2016.03.023

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