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The Size and Sign of a Spillover Effect of Organization Capital

Wen Chen

For additional information please contact:

Name: Wen Chen
Affiliation: University of Groningen

Email Address: wen.chen@rug.nl

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The Size and Sign of a Spillover Effect of Organization Capital

Wen Chen*

Faculty of Economics and Business

University of Groningen

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ABSTRACT

Intangible capital has gained increasing importance and popularity in recent years. In this study, the light is shed specifically on two widely acknowledged intangibles, namely R&D and organization capital. Rather than focusing on the impact of these two intangibles per se, the current research investigates their potential spillover effects. Using panel data on 2051 manufacturing firms, this paper finds robust evidence to support a positive spillover effect of R&D and a negative spillover effect of organization capital. More importantly, by interacting these spillover effects with industrial R&D intensities this paper verifies a positive relationship between the amount of spillovers and the degree of firms' R&D intensity. That is, more spillovers are taking place among firms that are more R&D intensive; while there is less spillover between less R&D intensive firms. These findings remain robust to a variety of alternative model specifications.

Key words: R&D spillovers; Organization capital; Production function estiamtion;

* PhD student at the Department of Global Economics and Management (GEM), Faculty of Economics and Business, University of Groningen, The Netherlands. E-mail: wen.chen@rug.nl

1. INTRODUCTION

Ever since the famous remark by Robert Solow made in 1987 that "you see computer revolution everywhere except in the productivity data" (Solow, 1987), there has been an ever-increasing recognition and interest in measuring intangible capital (e.g. software, R&D, and organization capital)[1]. Empirical researches relating intangibles to firm performance at the micro level or to economic growth at the macro level have both flourished in recent years (Black and Lynch, 2005; Lev and Radhakrishnan, 2005; Corrado, Hulten, and Sichel, 2009; hereafter CHS; Van Ark, *et.al,* 2009; Nakamura, 2010; Piekkola, 2011). Extensive evidence has been found to support the belief that intangibles have a positive impact on productivity and broader growth, reaffirming the increasingly important role of intangible capital in the modern economy. In addition to this growing strand of research, studies on examining the spillovers of R&D capital are also well established in the literature. Dating back to Griliches (1979), the level of productivity achieved by one firm or industry depends not only on its own research and development efforts but also on the level of the pool of general knowledge accessible to it. The current consent is that there is a significant positive spillover effect of R&D capital. This effect is also known as technology spillover and it can be beneficial both directly and indirectly. Direct benefits consist of learning about new technologies and materials. Indirect benefits, if we take an intra-country perspective, emanate from using higher quality of inputs that have recently been developed in the other sectors of the economy; or, if we take a global perspective it can originate from imports of goods and services that have been developed by trade partners (Coe and Helpman, 1995). The most recent attempt in probing the sign of R&D externalities is by Bloom *et.al* (2012). They extended the existing literature by examining what they call the business stealing effects rising from product market rivals, which is countervailing to the technology spillover of R&D. Using a panel of U.S. firms over the period of 1981 to 2001, both technology and product market spillovers of R&D are validated in their paper, but the former effect is found to be much larger than the latter (Bloom, *et.al*, 2012). That is to say, *technology* (i.e. positive) spillover remains to be the most prominent feature of R&D spillovers.

In sharp contrast, while being no less important than R&D capital since it is often found to be the most significant contributor to corporation's performance and growth (Arthur, 1994; Black and Lynch, 2005; Lev and Radhakrishnan, 2005), the potential spillover effect of organization capital have not yet received much attention. If firms can learn about new technologies and materials via a *technology* spillover of R&D capital, then it is in principal equally likely for firms to learn about new production process and/or more efficient organizational structures via (yet to be investigated) *knowledge* spillovers of organization capital. One good case in point is the just-in-time production process invented by Japanese car manufactures, which results in much higher production efficiency. Not only did other automakers from around the world devote vast efforts over the past two decades to learn or even imitate these systems, but firms with a different market-orientation (e.g. Harley

[1] Lev (2005) broadly defines intangibles as assets that lack physical substance but have great capacity to generate future profits. Of the readily identified intangibles, software, R&D and organization capital are among the most important constituents.

Davidson) adapted to this production process as well[2] (Lev and Radhakrishnan, 2005). Another example of a potential knowledge spillover effect of organization capital can be found in the information technology (IT) industry. Dell's pioneering build-to-order (BTO) distribution system where customers design their products via online ordering allowed Dell to outperform its competitors in personal computers. However, not long after the debut of the BTO system by Dell, other competitors (e.g. Compaq) promptly followed suit. They quickly realized that agility achieved by employing the BTO system has become one of the main competitive edges in staying competent in the market. This is especially true in a globalizing world where products become increasingly easy to be sold and bought online (Gunasekaran and Ngai, 2005).

Having said that, we shall not forget that the major components of organizational investment are used for advertisement, brand enhancement and on-the-job training, which all aim at increasing the market share can be captured by a firm. This implies that in the context of a single global market, the expansion in market share by one firm can only take place at the expense of the others. Thus, similar to the countervailing effects of R&D spillovers (with the positive effect being dominant), it is likely to observe a negative spillover effect of organization capital. As will be argued later in this paper, a *knowledge* spillover of organization capital is highly limited due to its extreme tacitness nature. Thus, if any spillover effect of organization capital can be identified it is more likely to be the negative spillover than otherwise.

With the inclusion of a multitude number of manufacturing industries, we further contribute to the literature by probing whether the magnitude of technology spillover of R&D depends on the R&D intensity of an industry. As the survival and success of firms that belong to more R&D intensive industries are critically dependent on the innovative products and technologies they produce. If there is a novel technological breakthrough achieved by one firm the other competitors in the same field need to respond promptly by at least mastering, if not improving upon, this technical advancement so as to stay competitive in the market.[3] On the contrary, for firms that come from less R&D intensive industries, the goods they produce typically have minimal technological embodiment. Consequently, the magnitude of technology spillovers should accordingly be smaller.

Along similar lines of reasoning, this paper extends the investigation to include one more interaction term: organization capital and industrial R&D intensity. Unlike those highly R&D intensive firms where competition is largely innovation driven, less R&D intensive ones might instead sustain their competitive edge through organization capital (Lev and Radhakrishnan, 2005). The opposing conjecture, however, seems equally plausible (if not more) since high-tech firms need to *internally* spend more to train its employees to get acquaint with the products and/or services they sell (i.e. on-the-job training) and externally more advertising is required in order to introduce those newly developed products and/or services to the potential customers. In a medical study, Gagnon and Lexchin (2008) show that while being highly R&D intensive pharmaceutical firms *de facto* spend about twice as much on advertising (one of the three major components of organization capital) as

[2] To fully implement the just-in-time production process, the American car manufacture, General Motor, even set up a joint production facility (GM-Toyota) Nummi plant in Freemont, California.

[3] The tablet computer market reinvigorated by Apple Inc. in recent years is a good case in point. By introducing iPad to the market other competing firms, notably Samsung and Blackberry, quickly followed suit by releasing their own version of tablets so as to remain competitive in electronics industry.

they do on research and development. As a result, the direction of this interaction effect is not as clear-cut as R&D's technology spillover. It can go either way and which one of the two dominates is subject to empirical examination in this paper.

Using financial data for a panel of 2051 publicly listed firms over the time period of 1992 to 2011, this paper reaffirms the positive spillover effect of R&D capital in technology space and similar to the findings of Bloom *et. al* (2012) there is also evidence, though somewhat weaker, supporting the existence of a negative effect of R&D spillover rising from the product market rivals. By augmenting the production function to further include organization capital, a negative spillover effect is identified for technologically similar firms and this finding is robust to a wide range of sensitivity checks. Contrary to prior expectation, however, this paper fails to validate a negative spillover effect of organization capital in the market space, though it takes the expected negative sign but it is statistically insignificant even at the generous 10 per cent level. This might imply that the proximity measure of firms' closeness in the market space is rather over-simplified in this paper. Firms are assumed to be either identical or no similarities at all, leaving no variations in between. In contrast this rather dismal finding in the market space, investigation of spillovers in the technology space yields much more fruitful results. By interacting the effect of technology spillover with industrial R&D intensity, this paper further validates the conjecture that the effect of R&D technology spillovers is much stronger for highly innovation-driven firms; while the magnitude of this spillover is much smaller for less innovation-driven ones. Similarly, the negative organizational spillover also tends to be stronger for more R&D intensive firms than those less intensive ones.

The remainder of this paper is organized as follows. We begin with a thorough review on the definition of organization capital and its associated features in section 2. Then, in section 3 we present a more in-depth discussion on the data and method used to measure R&D and organization capital. How are they converted to capital stocks, and how the econometric models are constructed. Empirical results, main findings and robustness checks are presented and discussed in section 4. Section 5 offers concluding remarks.

2. WHAT IS ORGANIZATION CAPITAL AND THE ASSOCIATED FEATURES?

Before any of the hitherto questions can be addressed it is crucial to first understand what is meant by organization capital and what are the associated features. An early paper written by Presecott and Visscher (1980) defines organization capital as an informational asset that affects the production possibility set of a firm and is produced jointly with output. Though there is not yet a consensus definition, but this firm-embodied concept of organization capital enjoys popular support among scholars.[4] The proponents of this view include Arrow (1962), Rosen (1972), Tomer (1987), Ericson and Pakes (1995), Atkeson and Kehoe (2002), and Eisfeldt and Papanikolaou (2011). Despite of the differences in their formulations, the core in defining organization capital is invariably the same: "it is an agglomeration of knowledge that is used to combine human skills and physical

[4] Some other researchers regard organization capital as embodied in employees. For instance, Jovanovic (1979) and Becker (1993).

capital into systems for producing and delivering want-satisfying products" (Evenson and Westphal, 1995). Thus, organization capital can provide firms with a competitive edge to consistently and efficiently extract from a given level of physical and human resources a higher value of output than what is possible to attain in the absence of such a capital. This highly productive nature of organization capital is also empirically proven. According to the estimates by Eisfeldt and Papanikolaou (2011), firms with more organization capital relative to their industry peers outperform those with less organization capital by 4.8 per cent per year.

Like any other types of intangibles organization capital is also characterized by the features of non-rivalness and non-excludability. This means that the marginal cost for an additional firm or individual to use the knowledge is often negligible. However, unlike R&D capital which mostly results in new technologies that are patentable, the out-product of organization capital often cannot be patented.[5] As a result, the partial tacitness of organization capital becomes critically important since such non-codifiability feature ensures that the resulting benefits of organization capital can only be *fully* or *largely* realized by those who have generated them. That is to say, two producers with identical material inputs in conjunction with fully symmetric market information, they may nonetheless end up with dramatically different productivity levels by employing what really are two distinct techniques due to differences in understanding of the tacit elements (Evenson and Westphal, 1995). An empirical example from the automotive industry perhaps best exemplifies this point. With the earnest efforts of adapting to the efficient just-in-time production process over an extended period of time, Japanese car manufactures nonetheless remain to be the world leaders in efficiency, profitability and quality (Lev and Radhakrishnan, 2005). In light of this real-life observation and the theoretical underpinning we come to the conjecture that the *knowledge* (i.e. positive) spillover of organization capital remains plausible in theory but it is with petite likelihood to be observed in practice. A negative spillover effect of organization capital, on the other hand, seems more likely to be empirically proven since organizational investment embodies all the expenses that are aimed at increasing the market share of a firm, which immediately hurts the sales of other firms.

One more important feature to note about organization capital is the speedy rate of obsolescence. Generally speaking, any capital–being it tangible or intangible–is subject to the loss of value once there is a reduction of future returns and it cease to exist as an economic good if such returns start to fall below the cost of producing and operating the capital (Gorzig, *et. al*, 2011). In contrast to tangible capital that depreciates due to physical tear and wear, intangibles depreciate due to obsolescence rising from competitions. This is especially true in a knowledge economy where technological inventions and novel ideas are the main ingredients of the modern knowledge society. According to estimation, organization capital is found to amortize at a rate around 25 per cent (Riley and Robinson, 2011; Gorzig, *et.al,* 2011). This rate is not only much higher than the usual rate used to depreciate physical capital which mostly fall in the range of 1 per cent to 15 per cent (Fraumeni, 1997), but it is also higher than the amortization rate of R&D capital which is estimated to be around 20 percent (CHS, 2006).

These depreciation rates are relevant when the measurements of R&D and organization capital are discussed in the following section in which the latter is measured using two distinct

[5] Trademarks and copyrights are two exceptions.

approaches. One is the firm-specific measurement of organization capital developed by Lev and Radhakrishnan (2005) and the other is a simple imputation procedure used in Hulten and Hao (2008).

3. DATA AND METHODS

3.1 Datastream and patents data

To enable estimation on the firm-level spillovers it is essential to develop a measure to proxy for the closeness between firms. Similar to the paper by Bloom *et.al* (2012) two proximity dimensions are identified, namely technological and market dimensions. This paper utilizes information on patents as the proximity measure for technological closeness and relies on industrial classification codes to measure for market closeness. Although it would have been preferred to have data on as many companies as possible, only 7389 publicly listed manufacturing firms have patents data available on the Bureau van Dijk (i.e. Orbis) database. Thus, these firms serve as the starting sample size, followed by the collection of the corresponding financial data in Datastream.[6] To be specific, we obtain data on R&D spending (WC01201), number of employment (WC07011), total sales (WC01001), net property, plant, and equipment (WC02501), and the selling, general and administrative expenses (WC01101) from Datastream. Since the focus of this research lies predominantly on organization capital, it is therefore essential for us to target on firms that have a relatively consistent and accurate record of investment in organization capital. According to Lev and Radhakrishnan (2005), large enterprises (e.g. sales value larger than $5 million) are more likely to have the accounting system that systematically track and record all investment in organization capital. Therefore, to avoid insignificant enterprises the sample data used in this paper consists of firms that have sales value greater than 5 million US dollars. One side benefit of applying this constraint is that it helps to get rid of companies that report insensible (sales) numbers (e.g. negative sales value or sales value of 1 dollar). Furthermore, to ensure a reasonable length of the time-series data firms that have any of the data items less than five observations are also excluded from the analysis. Complying with these criteria the final data sample of this paper contains 2051 manufacturing firms over a time-span of 20 years (i.e. 1992-2011).

3.2.1 Measuring Organization Capital

As discussed earlier, we opt for the firm-specific measuring approach developed in Lev and Radhakrishnan (2005) to gauge organization capital and only use the imputation procedure employed in Hulten and Hao (2008) as a validity check. We relate investment in organization capital to firm's spending on SGA expenses, since this major income statement item includes most of the expenditures that generate organization capital. One last thing to note before we proceed, SGA expenses retrieved from Datastream are denominated in nominal terms. In order to ensure comparability we first discount the prices using the implicit GDP price deflator provided by the

[6] Orbis also provides financial data at the firm level, but it only has a time span of 10 years which is much shorter than what Datastream offers. Moreover, as the key variable of interest SGA is not provided in Orbis database, but it is in Datastream. For these two reasons, we opt for Datastream as the main source to retrieve financial data.

Bureau of Economic Analysis (BEA). Following Lev and Radhakrishnan (2005), we drive the coefficients of investment in organizational capital using the two-stage least squares cross-sectionally for each sample year and industry[7]:

$$\log\left(\frac{Sales_{it}}{Sales_{i,t-1}}\right) = b_{0t} + b_{st}log\left(\frac{SGA_{it}}{SGA_{i,t-1}}\right) + b_{1t}log\left(\frac{PPE_{it}}{PPE_{i,t-1}}\right) + b_{2t}\log\left(\frac{EMP_{it}}{EMP_{i,t-1}}\right) + b_{3t}\log\left(\frac{RND_{it}}{RND_{i,t-1}}\right) + \log\left(\frac{e_{it}}{e_{i,t-1}}\right) \quad (1)$$

$$\log\left(\frac{SGA_{it}}{SGA_{i,t-1}}\right) = b_{0t} + b_{1t}log\left(\frac{Sales_{it}}{Sales_{i,t-1}}\right) + b_{2t}\log\left(\frac{SGA_{it-1}}{SGA_{i,t-2}}\right) + \log\left(\frac{\mu_{it}}{\mu_{i,t-1}}\right) \quad (2)$$

With 20 years spanning and twelve industry groups we derive 240 estimates from expression (1). To convert these coefficient estimates back to monetary values, Lev and Radhakrishnan (2005) defined the following two expectations of firm's output: one with both common (i.e. b_{0t}) and firm-specific (i.e. b_{st}) organization capital estimates and one with none of them:

$$Sales_{it}^{OC} = Sales_{i,t-1}\exp\left[b_{0t} + b_{0st}\log\left(\frac{SGA_{it}}{SGA_{i,t-1}}\right) + b_{1t}\log\left(\frac{PPE_{it}}{PPE_{i,t-1}}\right) + b_{2t}\log\left(\frac{EMP_{it}}{EMP_{i,t-1}}\right) + b_{3t}\log\left(\frac{RND_{it}}{RND_{i,t-1}}\right)\right] \quad (3)$$

$$Sales_{it} = Sales_{i,t-1}\exp\left[b_{1t}\log\left(\frac{PPE_{it}}{PPE_{i,t-1}}\right) + b_{2t}\log\left(\frac{EMP_{it}}{EMP_{i,t-1}}\right) + b_{3t}\log\left(\frac{RND_{it}}{RND_{i,t-1}}\right)\right] \quad (4)$$

where the difference between equations (3) and (4) is the measure of the value of the firm's investment in organization capital (i.e. *OC*= $Sales_{it}^{OC} - Sales_{it}$).

Since the investment in organization capital can be counterproductive to sales in certain years, we find that about 30 per cent of our estimates have negative OC values, which is comparable to the 25 per cent found in Lev and Radhakrishnan's (2005) paper. It worth to note, however, that the negative values only imply the contribution of organization capital to sales could be negative, but the amount of organization capital a firm possesses cannot be negative. Thus, the estimates of OC investment are multiplied by minus one if firm *i* in year *t* take a negative value. In doing so, we are implicitly assuming that the monetary benefits of investing in organization capital are fully reflected in firm's reported sales. This is admittedly a rather strong assumption to work with, but it is not without any plausibility since investment in R&D yields, on average, the cost of capital (Chan, *et.al*, 2001; Hall, 1993). To convert the investment numbers in to capital stocks we follow the usual perpetual inventory method:

$$K_{it}^{OC} = I_{it}^{OC} + (1-\delta^{OC})K_{i,t-1}^{OC} \quad (5)$$

where I_{it}^{OC} is firm *i*'s investment in organization capital at time *t*; δ^{OC} is the rate of depreciation which is set to 0.25 following the literature; $K_{i,t-1}^{OC}$ is the stock of organization capital that carried over from last year. To compute for the initial stock we follow the approach used in Gorzig (2011)

[7] We only outline the major equations used in Lev and Radhakrishnan (2005) to briefly illustrate how organization capital is measured. Please refer to their paper for detailed discussions on this firm-specific approach of measuring organization capital.

and Riley and Robinson (2011) where the initial stocks are assumed to be proportional to the sample average of investment. That is:

$$\mathrm{K}_{i,2001}^{OC} = \bar{I}_{i}^{OC} * \frac{1-(1-\delta^{oc}-g)^{T}}{1-(1-\delta^{oc}-g)} \qquad (6)$$

where T and g is set to 100 and 0.02, respectively. $\bar{I}_{i}^{OC}$ is the sample average of investment in OC and g is the growth of investment in the years before 1992. As explained in Gorzig (2011) that T should be infinite in theory but for practical purposes setting it to 100 is sufficient. Please refer to the right panel of table 3 in appendix A for a detailed summary statistics of organization capital.

To ensure the validity of our OC estimates, we apply the imputation procedure used in Hulten and Hao (2008) as an alternative measure for organization capital. The imputation procedure calculates the value of organizational investment as a fraction of 30 per cent of the firm's SGA outlays. Similar to what has been done in translating the investment numbers to capital stocks before, the exact same converting procedure is applied again. The correlation between the organization capital derived using Lev and Radhakrishnan's approach (OC^{LR}) and the simple imputation approach (OC^{HH}) is about 0.61, lending moderate support to the validity of the OC^{LR} estimates. Moreover, OC^{LR} is on average 4.6 times larger than the OC^{HH} estimates. This is no particular surprise since the imputation procedure used in Hulten and Hao is translated from the estimates developed by Corrado, Hulten and Sichel (2005), which are in the eyes of Prescott (2005) too small a number. It is also acknowledged by the authors (i.e. CHS) that in light of the famous dictum made by John Maynard Keynes: "it is better to be vaguely right than precisely wrong" they have chosen to err on the safe side in measuring investment in intangible capital.

3.2.2 Measuring R&D Capital

To compute for R&D capital, we first discount the reported R&D expenses as well using the implicit GDP price deflator proved by BEA. As suggested by the literature that R&D capital amortize at a rate of 20 per cent, we then follow the perpetual inventory method to covert the investment numbers in to stocks. In equation terms:

$$\mathrm{K}_{it}^{RD} = I_{it}^{RD} + (1-\delta)K_{i,t-1}^{RD} \qquad (7)$$

where $K_{i,t-1}^{rd}$ denotes the stock of R&D in year *t-1*, I_{it}^{rd} represents the amount of investment of R&D in year *t*, and δ is the rate of depreciation which is set at 20 per cent. One more step required *a priori* is to derive the stock of R&D at the starting year (i.e. 1992). Similarly, the initial stock of R&D is computed as:

$$\mathrm{K}_{i,2001}^{RD} = \bar{I}_{i}^{RD} * \frac{1-(1-\delta-g)^{T}}{1-(1-\delta-g)} \qquad (8)$$

where, ceteris paribus, only the superscripts have changed to R&D in going from equation (6) to (8).

3.3 Calculate the values of R&D Intensity of Industries

For each industry's R&D intensity we rely on the data provided by OECD STAN database. Two different measures on R&D intensity are provided for the manufacturing sectors in the period of 1995 to 2008. One is *R&D intensity using production* and the other is *R&D intensity using value-added*. Since the variation across industries' intensity does not differ much between these two, we arbitrarily opt for the latter indicator.[8] One caveat to note is that the industrial R&D intensity here is computed based on the data of one single country (i.e. U.S.), which is selected for its better data availability. In other words, the degree of R&D intensity of an industry computed in this paper does not differ across countries. That is to say, the pharmaceutical industry in the U.S. is assumed to be just as R&D intensive as the pharmaceutical industry in China.

Given the fact that industrial R&D intensity values vary (slightly) over time, to smooth out the time-series changes and have a single constant intensity indicator for each industry, we compute an average value of R&D intensity as follows: $\text{R\&D}_{it}^{U.S.} = \sum_{t=1}^{14} R\&D_{it}^{U.S.}/14$; where *i* and *t* denotes industry and year, respectively; the denominator is the time span of 14 years (i.e. 1995-2008) . Please refer to table 2 appendix A for more details on the level of the industry-specific R&D intensities.

3.4.1 Proxy firm's closeness in technology space using patents

Information on patents is used to proxy for the distance measure between firms. In other words, two firms are assumed to be closer to each other if more of their historically obtained patents fall under the same technology class. Using international patents classification code (IPC), 638 different technology categories can be identified. If firm A have obtained patents in, say, 100 different technology classes out of the total of 638, then we label a value of one under these technology classes, indicating that this firm is operating in these technological domains; while for the rest 538 technology classes we label a value of zero. Repeat this for all the firms gives us a vector $T_i = (T_{i1}, T_{i2}, T_{i3} \ldots T_{i638})$ where $T_{i\tau}$ indicates whether or not firm *i* operates in technology class τ. Following Jaffe (1986), firm's closeness is then calculated as the uncentered correlation between all firm *i*, *j* parings:

$$Tech\ Closenss_{i,j} = \frac{T_i T_j'}{(T_i T_i')^{\frac{1}{2}} (T_j T_j')^{\frac{1}{2}}} \qquad (9)$$

computing equation (9) gives us a measure that ranges from zero to one. The higher the degree of overlap in technology classes, the larger the value of closeness. This measure is also symmetric to firm ordering so that $Closenss_{i,j} = Closenss_{j,i}$. Along similar lines of Bloom *et.al* (2012), the pool of technology spillover of R&D and organization capital is then calculated as:

$$Tech\ Spillover_{it}^{RD} = \sum_{j,j\neq i} TechCloseness_{ij} * G_{jt}^{RD} \qquad (10)$$
$$Tech\ Spillover_{it}^{OC} = \sum_{j,j\neq i} TechCloseness_{ij} * G_{jt}^{OC} \qquad (11)$$

As can be read from the superscripts, G_{jt}^{rd} and G_{jt}^{OC} indicate the stock of R&D and organization capital, respectively.

[8] In retrospect, the results derived in this paper do not differ if the former R&D intensity indicator is used.

3.4.2 Proxy firm's closeness in market space using NACE codes

Similarly, with the NACE rev.2 at 4-digits codes provided by Orbis firms are assumed to be closer in the market space if they have the exact same 4-digits code. There are in total 231 manufacturing industry classes identified in NACE rev.2 classification and firms get a value of one in its own operating class and zeros in others. Repeat this for all the firms gives us another vector $T_i = (T_{i1}, T_{i2}, T_{i3} \ldots T_{i231})$ where $T_{i\tau}$ indicates whether or not firm *i* operates in industry class *τ*. Similar to the earlier attempt, firm's market closeness is then calculated as:

$$Market\ Closenss_{i,j} = \frac{T_i T_j'}{(T_i T_i')^{\frac{1}{2}} (T_j T_j')^{\frac{1}{2}}} \qquad (12)$$

computing equation (12) provides us with a matrix of zeros and ones. That is to say, firms are considered to be either perfectly similar or no similarities at all. One caveat to note with this measure is that no variation is allowed in between. Firms with the classification codes 2612 are as dissimilar as firms with code 1189 to a firm coded 2611. Multiply this matrix with the firm-specific R&D and organization capital we obtain the following two market spillover variables:

$$Market\ Spillover_{it}^{RD} = \sum_{j,j\neq i} MarketCloseness_{ij} * G_{jt}^{RD} \qquad (13)$$
$$Market\ Spillover_{it}^{OC} = \sum_{j,j\neq i} MarketCloseness_{ij} * G_{jt}^{OC} \qquad (14)$$

As usual, G_{jt}^{rd} and G_{jt}^{OC} indicate the stock of R&D and organization capital, respectively.

3.5 Model Specifications

In this subsection we discuss how the econometric models are constructed in this paper. First, we start out with the conventional two-factor Cobb-Douglas production function which takes the following generic form:

$$Y_{it} = A \cdot K_{it}^{\beta_1} \cdot L_{it}^{\beta_2} \qquad (15)$$

where *A* is the state of technology, *K* denotes capital inputs and *L* is the labor inputs. Transforming the equation into log terms yields:

$$y_{it} = \beta_1 k_{it} + \beta_2 l_{it} + \mu_{it} \qquad (16)$$

Estimating this equation would help one to explain how much of the growth in output (i.e. sales) can be attributed to additional use of physical capital, how much is due to a rise in employment and how much is left to be explained by the total factor productivity (TFP) A_{it}. With the conversion of R&D and organizational investment in to capital stocks, we extend this benchmark production equation to include these two extra inputs:

$$y_{it} = \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 k_{it}^{RD} + \beta_4 k_{it}^{OC} + \mu_{it} \qquad (17)$$

In principal, one would expect that the estimation of equation (14) should downsize the role played by TFP (i.e. μ_{it}) than estimating equation (13), since less variables are embedded in the error term.

Using the same analytical framework developed in Bloom *et.*al (2012) what we are really interested in is the estimation of the following relationship:

$$\begin{aligned} lnY_{it} = \alpha + \beta_1 lnK_{it-1}^{RD} + \beta_2 lnK_{it-1}^{OC} + \beta_3 ln\, TechSpillover_{it-1}^{RD} + \beta_4 ln\, TechSpillover_{it-1}^{OC} \\ + \beta_5 ln\, MarkectSpillover_{it-1}^{RD} + \beta_6 ln\, MarketSpillover_{it-1}^{OC} + \beta_7 X_{it} + \varepsilon_i + \tau_t + v_{it} \end{aligned} \quad (18)$$

where four spillover terms are introduced to the model; X contains the control variables, namely labor and physical inputs; ε_i is the firm specific effect, τ_t is a full set of time dummies, and v_{it} is the idiosyncratic error term. The main variables of interest are the coefficients of β_3, β_4, β_5, and β_6 as they determine both the sign and size of a spillover effect of R&D and organization capital. In the technology space, we would expect to find a positive sign (i.e. $\beta_2>0$) for R&D capital since one firm can benefit from the research efforts of the other firms. A negative sign (i.e. $\beta_3<0$) is expected for organization capital as firms will be adversely affected if other technologically similar firms incur more costs to build up their organizational capital stock, which expands the market share at the expense of the others. In the market space, both β_5 and β_6 are expected to take negative signs since firms are competing in this dimension.

If any of the spillover effects is identified using equation (18) we then further extend it by adding four more interaction terms so that we are enabled to examine whether the degree of the spillover effect differ depending on the R&D intensity of an industry. Therefore, the second model of main interest takes the following form:

$$\begin{aligned} lnY_{it} = \alpha + \beta_1 lnK_{it-1}^{RD} + \beta_2 lnK_{it-1}^{OC} + \beta_3 Tech\ Interaction_{it-1}^{RD} + \beta_4 Tech\ Interaction_{it-1}^{OC} \quad (19) \\ + \beta_5 Market\ Interaction_{it-1}^{RD} + \beta_6 Market\ Interaction_{it-1}^{OC} + \beta_7 X_{it} + \varepsilon_i + \tau_t + v_{it} \end{aligned}$$

where the interaction terms are computed as follows:

$$\begin{aligned} Tech\ Interaction_{it-1}^{RD} &= ln\ TechSpillover_{it-1}^{RD} * Industrial\ R\&D\ intensity\,; \\ Tech\ Interaction_{it-1}^{OC} &= ln\ TechSpillover_{it-1}^{OC} * Industrial\ R\&D\ intensity\,; \\ Market\ Interaction_{it-1}^{RD} &= ln\ MarketSpillover_{it-1}^{RD} * Industrial\ R\&D\ intensity\,; \\ Market\ Interaction_{it-1}^{OC} &= ln\ MarketSpillover_{it-1}^{OC} * Industrial\ R\&D\ intensity\,; \end{aligned}$$

Moreover, for ease of exposition X_{it}, in addition to containing physical capital and labor as control variables, includes four spillover terms as well.

4. EMIRICAL RESULTS

4.1 Production function estimates without spillovers

The left panel of each column shown in table 4 (appendix A) summarizes the results for the simple regression model of a two-factor production function. With no surprise, both labor and capital inputs are found to be highly significant in predicting firms' output. By augmenting the model to include R&D and organization capital, the model of fit improves as both variables turn out to be significant predictors, which also legitimizes the inclusion of these two intangible assets into the model. Moreover, the intangible-augmented model expectedly assigned a smaller role to TFP in explaining output growth. This finding conforms to the rapid rising literature in recognizing the need to treat intangible investment on an equal footing as tangible counterparts (CHS, 2009; Van Ark *et,al.*, 2009). In the presence of potential simultaneous bias as it was first pointed out by Marschak and Andrews (1944), the coefficients estimated need to be interpreted with great caution. According to Levinsohn and Petrin (2003) the simultaneous bias of the production function estimation has two consequences. If physical capital has no correlation with labor units, then coefficient estimate on labor tend to be biased up while leaving the coefficient estimate of capital unbiased. In the second scenario, if there is a positive correlation between physical capital and labor, the capital coefficient will be underestimated. Having a positive correlation between K and L (i.e. 0.31) in our sample, the only bias in the estimates shown in table 4 is no more than an underestimated effect of physical capital. This bias can be problematic if the prime goal of one's research is to deriving an accurate estimate for the efficiency term A_{it} (Van Beveren, 2012). Since the focus of the current research lies on the coefficient estimates of those spillover terms, thus the simultaneity problem should not cause great concern here.

4.2 Production function estimates with spillovers

Table 5 (Appendix A) summaries the results for the model augmented with the spillover terms. In line with the prior expectations, the spillover effect in the technology space takes the expected signs. That is, there is a significant positive technology spillover of R&D capital and a negative spillover effect of organization capital. According to estimation, a one per cent rise in the level of the pool of general knowledge leads to 0.077 per cent rise in firms' sales. By comparison, organizational spillovers are much smaller in magnitude, which is about one-half of that of R&D. To be precise, a one per cent rise in the investment pool of organization capital leads to 0.037 per cent decrease in the sales of another firm. In contrast to this encouraging finding in the technology space, spillovers in the market space seem rather dismal. Although both β_5 and β_6 take the expected negative signs, it is insignificant even at the generous 10 per cent level (column 3, table 5). This seems to conform to the prior fear that the proximity measure of market closeness, as opposed to technology, is over-simplified. Firms are measured to be either fully competing or not competing at all, leaving no variations in between.

To gain more insights we repeat the same regression analysis for each and every industry to further check whether consistent findings emerge. As can be seen from table 6 (appendix A) the results are generally comforting. Despite of the contradicting signs appearing occasionally, all the significant effects take the expected signs. That is, only the *positive* R&D technology spillover effect and the *negative* organizational spillover effect are found to be statistically significant (table 6, Appendix A). Again, the spillover effect in the market space remains to be unfruitful at the more disaggregated industry-level. One more interesting observation to note in table 6 is that, as the most R&D intensive industry included in the paper Pharmaceutical industry features the strongest R&D technology spillover effect. This observation seems to be consistent with the conjecture that higher R&D intensive industries feature a stronger spillover effect.

4.3 Marginal effects of spillovers

To probe whether spillovers indeed differ in magnitude depending on an industry's R&D intensity, we interact the industrial R&D intensity values with the spillover terms and include these interactions in the model. Results are shown in table 7 (appendix A). Both marginal effects are found to be statistically significant. In plain words, a greater spillover effect is identified for more R&D intensive industries than less R&D intensive ones, and this relationship holds true for both R&D technology and organizational spillovers. These results can be best visualized in appendix B where the left panel of graph 1 shows a clear upward trend in the level of R&D spillovers as industries become more R&D intensive. While in the right panel, we can see a clear "reversed upward" sloping trend (since the organizational spillover takes a negative sign), indicating that the higher the intensity value of an industry, the more the firms are adversely affected by other firms' organizational investment. In other words, in order to attract more customers firms that are highly innovative incur more costs in branding the goods and/or services they produce, thereby hurting the other technologically similar firms.

4.4 Robustness checks

To further validate these obtained results we employ a number of sensitivity checks. First, following the suggestions by Bloom *et.al* (2012) we use an alternative specification that introduces current (rather than lagged) values of the four spillover measures, and estimate it by instrumental variables using lagged values as instruments. As shown in column 4 (table 4, Appendix A), this approach does not only produce similar results but it also identifies a negative effect of R&D spillover in the market space, which we fail to validate in earlier attempts. The organizational spillover in the market space remains insignificant.

The other robustness check we perform is to replace *log(sales)* with *log (sales/emp)* as the dependent variable, and all inputs on the right hand side of the equation are transformed in per employee terms as well. Results of this specification are shown in column 5 (table 4, Appendix A). The findings remain consistent, and the only difference is that R&D technology spillover becomes even stronger and organizational spillover becomes somewhat weaker than the original specification. Moreover, with all variables denominated in per employee terms the marginal effects of the spillovers in the technology space are perfectly in line with the earlier findings too (see column 3, table 7).

5. CONCLUSIONS AND DISCUSSIONS

Business investments in intangibles have undoubtedly a great impact on firms' productivity and broader growth. However, in addition to the direct benefits that firms can avail from their own research endeavors there are also spillovers coming from the efforts of other firms that operate in similar technological domains. Using a panel of financial data of 2051 publicly listed firms over a 20 year time-span (i.e. 1992-2011), it is reaffirmed with robust evidence that there is a highly significant technology spillover effect of R&D capital. Employing the instrumental variable approach as suggested by Bloom *et.al* (2012), there is also evidence confirming the newly discovered negative spillover effect of R&D rising from product market rivals. By adding an interaction term between technology spillover and industry's R&D intensity, we find robust evidence to validate the conjecture that more technology spillovers are taking place in more R&D intensive industries. As a novel addition to the existing literature, this paper provides strong evidence to verify the existence of a negative organizational spillover effect between technologically similar firms. That is to say, while firms can benefit from the technology pool, they are nevertheless hurt when other firms increase their level of organizational investment. The size of this negative spillover, however, is about only half of that of the positive technology spillovers of R&D. Similarly, by interacting organizational spillover with industrial R&D intensity this paper also proves that a greater degree of organizational spillover is taking place in more R&D intensive industries.

Contrary to the fruitful findings in the technology space, we fail to find solid evidence to verify any spillover effect of organization capital in the market space. This might, as suspected, due to an over-simplified proximity measure of firms' market closeness, which assumes firms are either directly competing or not competing at all in the market, leaving no variations in between.

Despite of the contradicting signs appearing sporadically, these findings are largely consistent when the analysis is narrowed down to the industry level. The obtained results also remain robust to alternative specifications when instrumental approach is used and variables are transformed in per employee terms. These sensitivity checks further enhanced the validity of the findings. Admittedly, this study is subject to several methodological limitations, which require further improvements. First, an intermediate input measure (e.g. materials) is highly desired to be included in the production function as it would help to reduce omitted variable bias and give confidence in interpreting the coefficient estimates on capital and labor. Second, a more sophisticated proximity measure of market closeness is warranted. Ideally, a revised measure could disentangle firms' market closeness at a more detailed level, thereby capturing the degree of competitiveness between firms more accurately.

In conclusion, having the existence of a negative spillover effect of organization capital identified we add another novel perspective to the growth, productivity and industrial organization literature that has overlooked this potential spillover for too long.

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APPENDIX A– TABLES

Table 1 – Matching of Industry Classifications

NACE Rev.2 at 4-digits	OECD STAN	Name of Industry
1011- 1200	C15T16	Food products, beverages and tobacco
1310 - 1629	C17T19	Textile, textile products, and footwear
1711- 1820	C21T22	Pulp, paper, printing and publishing
2011- 2060	C24X	Chemicals without pharmaceuticals
2110 - 2120	C2423	Pharmaceuticals
2211- 2229	C25	Rubber and plastics
2311- 2399	C26	Other non-metallic mineral products
2410- 2599	C27T28	Basic and fabricated metal products
2811- 2899	C29	Machinery and equipment n.e.c.
2611- 2790	C30T33	Electrical and optical equipment
2910 - 2932	C34	Motor vehicles and (semi-) trailers
3011- 3099	C35	Other transport equipment

Table 2 – List of Industries and Distribution of Firms

	Number of Firms	Industrial R&D Intensity
Food products, beverages and tobacco	*57*	*1.14*
Textile, textile products, and footwear	*64*	*1.18*
Basic and fabricated metal products	*136*	*1.38*
Pulp, paper, printing and publishing	*43*	*1.40*
Other non-metallic mineral products	*41*	*1.89*
Rubber and plastics	*45*	*2.98*
Machinery and equipment n.e.c.	*293*	*6.65*
Chemicals without pharmaceuticals	*164*	*7.27*
Motor vehicles and (semi-) trailers	*76*	*15.01*
Other transport equipment	*14*	*25.18*
Electrical and optical equipment	*1004*	*26.32*
Pharmaceuticals	*114*	*33.41*

Note: R&D intensity indicators are calculated based on data from OECD Structural Analysis Statistics

Table 3 – Summary Statistics of R&D and Organization Capital

R&D Capital stock					Organization Capital stock				
	Percentiles	Smallest				Percentiles	Smallest		
1%	230	15			1%	4292	10		
5%	989.	16			5%	12235	33		
10%	1887	18	Obs	24520	10%	20156	50	Obs	20840
25%	4983	19	Sum of Wgt.	24520	25%	44730	85	Sum of Wgt.	20840
50%	**13133**		Mean	33057.36	**50%**	**100375**		Mean	271625
		Largest	Std. Dev.	74225.45			Largest	Std. Dev.	3374090
75%	33604	3387242			75%	211411	1.39e+08		
90%	83470	3552775	Variance	5.51e+09	90%	427404	1.85e+08	Variance	1.14e+13
95%	131892	3655635	Skewness	22.06419	95%	664546	2.47e+08	Skewness	74.45604
99%	276366	4138173	Kurtosis	1004.365	99%	1996606	3.28e+08	Kurtosis	6226.272

Table 4 – Production Function Estimates without Spillovers

	(1) OLS		(2) OLSD		(3) FE	
PPE	.372*** (84.76)	.309*** (79.09)	.325*** (39.1)	.233*** (27.67)	.325*** (21.73)	.233*** (11.76)
EMP	.346*** (62.94)	.205*** (39.07)	.370*** (33.3)	.256*** (25.6)	.370*** (17.38)	.256*** (8.57)
R&D		.087*** (30.14)		.128*** (10.95)		.128*** (3.75)
OC		.270*** (56.76)		.101*** (21.63)		.101*** (9.22)
SUM β	.718	.871	.695	.718	.695	.718
R^2	.63	.73	.92	.94	.50	.50
N	26436	20839	26436	20839	26439	20839

Note: All variables are transformed in to natural logarithms for regression. Absolute values of t-statistics, based on robust (cluster) standard errors, are shown in parentheses.
(1) Conventional OLS estimation;
(2) OLS estimation with country, industry, year and company dummies included;
(3) Fixed effects with time-specific dummies
***p<0.01, **p<0.05, *p<0.1

Table 5 – Production Function Estimates With Spillovers

	(1) OLS	(2) OLSD	(3) FE	(4) IV	(5) *FE*
PPE	.293*** (68.72)	.267*** (25.07)	.267*** (16.08)	.276*** (48.68)	.33*** (15.22)
EMP	.222*** (39.78)	.367 (24.38)	.367*** (14.22)	.210*** (36.27)	
R&D	.098*** (26.43)	.036*** (2.82)	.036 (1.5)	.095*** (19.02)	.030 (1.28)
OC	.262*** (52.84)	.065*** (14.18)	.065*** (8.67)	.315*** (39.81)	.058*** (7.94)
Tech-spillRD	.009 (.9)	**.076*** (3.29)**	**.077** (2.19)**	**.024* (2.02)**	**.168*** (5.39)**
Tech-spill^{OC}	-.057*** (6.08)	**-.037*** (4.58)**	**-.037*** (2.76)**	**-.075*** (6.80)**	**-.025** (1.95)**
Market-spillRD	-.046*** (5.69)	**-.039* (1.95)**	-.039 (1.01)	**-.047*** (4.74)**	.018 (.6)
Market-spill^{OC}	.013 (1.6)	**-.012* (1.68)**	-.011 (.99)	-.014 (1.44)	-.008 (.63)
R^2	.73	.93	.52	.75	.35
N	18893	18893	18893	16720	18893

Note: All variables are transformed in to natural logarithms for regression. Absolute values of t-statistics, based on robust (cluster) standard errors, are shown in parentheses. Column (1) reports the simple OLS estimation coefficients. Column (2) shows OLS estimation with country, industry, company, and year dummies included. Column (3) is the firm-fixed effects model. Column (4) is estimated by instrumental variables using lagged values as instruments. Column (5) shows the results obtained when regression is performed in *per employee* terms. ***p<0.01, **p<0.05, *p<0.1

Table 6 – Analysis per Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PPE	.348***	.367***	.235***	.197***	.264***	.471***	.355***	.194***	.279***	.153***	.292***	.249***
	(17.38)	(20.45)	(32.62)	(15.12)	(7.88)	(14.78)	(8.57)	(2.96)	(6.29)	(6.95)	(9.22)	(8.47)
EMP	.204***	.196***	.340***	.463***	.252***	.155***	.252***	.347***	.386***	.637***	.271***	.139***
	(10.65)	(8.9)	(37.34)	(23.56)	(9.54)	(5.48)	(8.03)	(5.02)	(8.38)	(15.6)	(7.04)	(4.9)
R&D	.042	.083***	.189***	.049*	.76	.089*	.143***	.105	.076	.046	.011*	.180***
	(1.58)	(3.8)	(11.15)	(2.09)	(1.52)	(2.31)	(3.43)	(.95)	(1.63)	(1.04)	(2.09)	(4.69)
OC	.054***	.107***	.128***	.086***	.018	.113***	.047*	.019	.129***	.128***	.088***	.072***
	(4.96)	(9.99)	(22.15)	(9.39)	(.95)	(6.93)	(2.41)	(.37)	(7.03)	(9.40)	(4.7)	(3.85)
Tech-spillRD	-.006	**.185****	.047	.103	.236	**.136*****	-.162	**.304****	-.462	**1.082*****	.018	.182
	(1.44)	**(2.03)**	(.53)	(1.78)	(1.70)	**(3.05)**	(.90)	**(2.81)**	(1.2)	**(3.48)**	(.09)	(1.43)
Tech-spill^{OC}	.039	-.005	**-.036***	-.015	.022	**-.175*****	.009	-.195	-.017	**-.159****	**-.126****	-.054
	(1.41)	(.2)	**(2.49)**	(.66)	(.68)	**(3.66)**	(.22)	(1.89)	(.41)	**(2.62)**	**(2.62)**	(1.07)
Market-spillRD	.139	.146	-.071	-.013	-.073	-.062	-.047	-.028	-.005	.151	.175	-.027
	(1.79)	(1.32)	(1.63)	(.32)	(.98)	(.51)	(.62)	(.15)	(.08)	(1.47)	(1.16)	(.54)
Market-spill^{OC}	.035	-.032	.004	**-.035***	-.028	.03	.061	.134	-.008	-.033	**-.103***	-.012
	(.92)	(1.16)	(.35)	**(2.06)**	(.9)	(.98)	(1.86)	(1.2)	(.24)	(1.23)	**(2.63)**	(.53)
R^2	.57	.61	.56	.50	.53	.69	.65	.72	.65	.67	.67	.49
N	1370	1873	9882	3124	598	748	483	133	442	1104	439	643

Note: (1) Basic and fabricated metals; (2) Chemicals; (3) Electrical and optical equipment; (4) Electrical machinery not classified elsewhere; (5) Food products, beverage and tobacco; (6) Motor vehicles; (7) Other non-metallic mineral products; (8) Other transport equipment; (9) Paper, printing and publishing; (10) Pharmaceuticals; (11) Rubber and plastics; (12) Textiles, leather and footwear.

***p<0.01, **p<0.05, *p<0.1

Table 7 – Marginal Effect of R&D and Organizational Spillovers

	(1) OLSD	(2) FE	(3) *FE*
Tech-spillRD * Intensity	**.005*** (3.62)**	**.005*** (2.30)**	**.007*** (3.20)**
Tech-spill^{OC} * Intensity	**-.001** (2.52)**	**-.001* (1.71)**	**-.001* (1.87)**
Market-spillRD * Intensity	.002 (1.56)	.002 (.97)	.003 (1.55)
Market-spill^{OC} * Intensity	.000 (1.00)	.000 (.64)	-.000 (.07)
R^2	.94	.52	.37
N	11893	11893	11893

Note: for conciseness estimates for the other variables are intentionally omitted and only those interaction terms are reported here. Column (3) reports estimation in *per employee* terms. ***p<0.01, **p<0.05, *p<0.1

APPENDIX B

Graph 1 - Marginal Effects of R&D and OC Spillovers