

Productivity spillovers of organization capital

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Abstract Investments in organization capital increase productivity of not just the investing firm but could also spillover to other firms—similar to investments in research and development. Recent evidence at the industry and economy level suggests such spillovers could be important. In this paper, we fail to find evidence of knowledge spillovers from organization capital that increase the productivity or market valuation of technologically similar manufacturing firms in the US. This lack of evidence at the firm-level suggests caution is in order at the more aggregate level, where spillover channels are harder to identify convincingly.

Keywords Organization capital · Intangible assets · Spillovers · Market value · Productivity

JEL Classification D24 · L22 · O33

1 Introduction

The role of knowledge-based assets for growth in advanced economies has drawn much recent interest from researchers and policy makers alike—see e.g. Corrado and Hulten (2010) and OECD (2013). But while researchers are rapidly incorporating such assets into a standard ‘sources-of-growth’ framework (e.g. Corrado et al. 2009, 2012), much is yet unknown about the productive impact of such

assets. Knowledge-based assets are typically intangible and thus non-rival and non-excludable. This opens up the possibility of knowledge spillovers (Nakamura 2010). In the case of research and development (R&D) spending, this has long been known (e.g. Griliches 1979, 1992) and recent firm-level evidence confirms the presence of R&D knowledge spillovers, see Bloom et al. (Bloom et al. 2013, BSV henceforth). But recent research has also shown knowledge spillovers from other knowledge-based assets, using industry-level data (Goodridge et al. 2012b, GHW henceforth) and economy-wide data (Corrado et al. 2014, CHJ henceforth).

In this paper, we are the first to test for the effects of knowledge spillovers from organization capital using firm-level data, rather than the more aggregated data that have been used so far.¹ Organization capital can be thought of as the information a firm has about its assets and how these can be used in production (Prescott and Visscher 1980). More specifically, it can be thought of as the value of brand names and knowledge embedded in firm-specific resources (Corrado et al. 2005).² Several studies have shown organization capital to be important for firm productivity³ and it also seems important for explaining stock market returns across firms (Eisfeldt and Papanikolaou 2013). Since

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¹ The literature on productivity spillovers from foreign direct investment (FDI)—e.g. Liu (2008) and Keller and Yeaple (2009)—is partly related since domestic firms could learn from the foreign multinational’s superior organization. However, any learning taking place could also be on aspects of the multinational’s productivity that are unrelated to organization capital.

² See also Atkeson and Kehoe (2005). Conceptualizing organization capital as *embedded* in the organization distinguishes it from measures of human capital, see e.g. Jovanovic (1979) and Becker (1993).

³ E.g., Tronconi and Vittucci Marzetti (2011), Hulten and Hao (2008) and Lev and Radhakrishnan (2005).

knowledge of, for instance, organizational structures is non-rival and non-excludable, knowledge spillovers *between* firms could, in principle, also be important.

Relying on firm-level analysis to identify the effects of knowledge spillovers has clear advantages over analysis based on more aggregate data. Most importantly, we can distinguish between the productivity effects of own-firm investments and knowledge spillovers between firms, while analysis of aggregate data does not allow for such a clear distinction. Another advantage is the greater number of observations, which allows for more stringent testing. There are also downsides to firm-level analysis, including a less precise delineation of what constitutes investment in organization capital. As we will argue later, though, the advantages outweigh the downsides.

In our analysis, we test whether firm productivity and market valuation are affected by the organization capital stocks of similar firms, defining ‘similar’ in the same way as BSV. Since organization capital relates to how production in a firm is organized, we expect that firms are more likely to learn and benefit from the investments of firms that are close in technology space. Firm profitability is likely to suffer, though, from investments in organization capital made by close competitors, i.e. firms that are close in product market space. By locating firms in these two spaces, we can distinguish between the two types of spillovers and provide estimates of the marginal private and social returns to organization capital investment.

We analyze a sample of 1266 US manufacturing firms over the period 1982–2011. We measure investment in organization capital as selling, general and administrative (SGA) expenses, an approach followed by many in the firm-level analysis of organization capital.⁴ Past investments are cumulated into a stock of organization capital and added to a production function with (tangible) capital and labor. The proximity of firms in technology space is determined using patent data—an approach pioneered by Jaffe (1986) in the context of R&D knowledge spillovers. We assume that firms with patents in similar technology fields have greater potential to learn from each other’s organization capital. One example of such a spillover is Toyota’s just-in-time system that quickly spread to other car manufacturers (Liker and Morgan 2006). An example of cross-industry diffusion is the build-to-order (BTO) distribution system that originated with Dell Computers, but that has since been copied by firms in other industries, such as BMW (Gunasekaran and Ngai 2005). Though patents may not perfectly reflect the scope for such copying, they may be useful in identifying the technological position of the firm in a broad sense.⁵

⁴ E.g. Eisefeldt and Papanikolaou (2013), Tronconi and Vittucci Marzetti (2011) and Hulten and Hao (2008).

Proximity in product market space is determined using the set of industries each firm is active in, assuming that greater overlap makes for fiercer competitors. Increased investment in organization capital by competitors is likely to hurt firm performance: competitors may have to devote resources to copying successful business models such as the BTO system. Investment in organization capital also includes spending on marketing and sales, and while some of this spending may expand the market, another part is aimed at capturing market share from competitors.⁶

Our findings are, first, that organization capital contributes substantially to the firm’s own productivity and market value and second, that investment in organization capital by firms that are close in technology space has no effect on firm productivity or market valuation. In contrast, we find results similar to BSV for R&D knowledge and market-rival effects. Following the approach of BSV, we find that the marginal private return to organization capital investments is positive, regardless of the chosen specification. The magnitude of the marginal social return is much more uncertain and could even be negative. Our results for organization capital are robust across industries and to alternative distance measures and assumptions regarding the capitalization of organization capital. We argue that these results make it unlikely that organization capital is the source of the knowledge spillovers found by CHJ and GHW. In the remainder of this paper we outline the methodology and data (Sect. 2), present the results (Sect. 3) and conclude (Sect. 4).

2 Methodology and data

In this section we discuss the econometric approach to analyzing organization capital spillovers, followed by a description of the data and the methods used to construct the measures of organization capital and the spillover pools.

2.1 Econometric specification

We analyze two firm-level outcome variables, namely productivity and stock market valuation. In order to establish the effect of organization capital and knowledge spillovers and market-rivalry effects on productivity, we estimate a production function; to establish the effects on firm’s market value, we estimate a market value equation.

⁵ In addition, some business methods can be and have been patented since the 1990s, see Hall (2009).

⁶ See Landes and Rosenfield (1994) on the long-lived nature of (some) advertising spending and, more broadly, Bagwell (2007) on the economics of advertising.

2.1.1 Production function equation

To estimate the effect of organization capital on firm productivity, we start from a Cobb–Douglas production function for firm i at time t , extended to include organization and R&D capital:

$$Y_{it} = A_{it}L_{it}^\alpha K_{it}^\beta G_{it}^\gamma R_{it}^\delta \tag{1}$$

where Y is a measure of output, A is Hicks-neutral technology, K is physical capital, L denotes labor input, G is the stock of organization capital and R is the stock of R&D capital. To determine the role of knowledge spillovers and any effects from product-market rivals, we log-differentiate Eq. (1) and estimate the following equation:

$$\begin{aligned} \log Y_{it} = & \gamma_1 \log G_{it} + \gamma_2 \log R_{it} + \varphi_1 \ln KH_{it}^G + \varphi_2 \ln MKT_{it}^G \\ & + \varphi_3 \ln KH_{it}^R + \varphi_4 \ln MKT_{it}^R + \omega X'_{it} + \eta_i + \tau_t + \varepsilon_{it}. \end{aligned} \tag{2}$$

Here KH_{it} capture knowledge spillovers from organization capital or R&D capital (distinguished by the superscripts G and R) and MKT_{it} denotes any market-rival effect of organization and R&D capital. This means that the technology term from Eq. (1), A , captures the effect from knowledge and market-rival spillovers; we further decompose technology into a correlated firm fixed effect (η_i), a full set of time dummies (τ_t), and an idiosyncratic component (ε_{it}) that is allowed to be heteroskedastic and serially correlated. Physical capital K and labor input L are combined into \mathbf{X}' . Note that we do not include a measure of material inputs, since fewer firms report on this item, thus reducing the sample size notably. However, we show in Appendix Table 11 that the main production function results are robust to whether materials are included or not.

Our main parameter of interest in this equation is φ_1 , which captures knowledge spillovers from organization capital. Based on the R&D spillover literature, we expect φ_3 to be significantly positive. BSV argue, based on the industrial organization literature, that φ_2 and φ_4 should be zero: organization or R&D capital of product-market rivals may hurt profitability due to loss of market share, but standard theories do not predict an effect on productivity.

The estimation of Eq. (2) can be affected by measurement error and simultaneity bias. Measurement error arises because firm sales are not deflated by a firm-level price index, but by an industry-level price index—obtained from the Bureau of Economic Analysis (BEA). When prices vary across firms within an industry, part of the variation in sales is due to variation in prices rather than quantities (Foster et al. 2008). To deal with this problem, we include the industry output index and price index as part of the control variables \mathbf{X}' , following the arguments of Klette and Griliches (1996) and De Loecker (2011). Simultaneity bias

causes concern because there might be unobserved productivity shocks that are known to the firms when they choose their input levels (Griliches and Mairesse 1998). The error term is assumed to include a firm fixed effect (η_i), because if the deviation between firm and industry prices is largely time-invariant, this should go a long way towards dealing with the problem of firm-specific prices. Moreover, to the extent that unobserved, firm-specific productivity is also time-invariant, the simultaneity problem should also be controlled for. As these assumptions might not hold in practice, we also consider a GMM specification, where lagged values of the explanatory variables are included as instruments.⁷

2.1.2 Market value equation

In estimating the effect of organization capital on firm market value, we also follow the approach outlined in BSV, but extended to include organization capital as another factor influencing firm market value as well as a possible source of spillovers. BSV, in turn, build on the work of Griliches (1981) in formulating their market value equation. Tobin’s Q, the firm’s market value over the book value of assets is used as the dependent variable and explained by organization and R&D capital, and spillover terms:

$$\begin{aligned} \ln \left(\frac{V}{A} \right)_{it} = & \ln \left(1 + \psi_1 \left(\frac{G}{A} \right)_{it} \right) + \ln \left(1 + \psi_2 \left(\frac{R}{A} \right)_{it} \right) \\ & + \lambda_1 \ln KH_{it}^G + \lambda_2 \ln MKT_{it}^G \\ & + \lambda_3 \ln KH_{it}^R + \lambda_4 \ln MKT_{it}^R + \omega \mathbf{X}'_{it} + \eta_i + \tau_t + \varepsilon_{it}, \end{aligned} \tag{3}$$

where V is the market capitalization of the firm (the value of common and preferred stock and total net debt) and A is the book value of its assets—including net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and capitalized intangibles, but excluding the (estimated) value of organization and R&D capital. Note that $\ln \left(1 + \psi_1 \left(\frac{G}{A} \right)_{it} \right)$ is a non-linear term and that both $\left(\frac{G}{A} \right)_{it}$ and $\left(\frac{R}{A} \right)_{it}$ are typically not small. A first-order approximation would thus not be accurate, so we use a higher-order expansion instead. As in the production function estimation, any knowledge spillovers from organization capital (λ_1) and from R&D capital (λ_3) should have a positive impact on Tobin’s Q. Unlike productivity, Tobin’s Q would be affected if successful innovations from R&D and organization capital of competitors were to reduce the

⁷ But note that given our long time period, with approximately 16 years of a data for the average firm, the bias of the OLS fixed effects estimator on the variables that are not strictly exogenous but only weakly exogenous is likely to be small.

Table 1 Descriptive statistics

	Median	Mean	SD	Between SD	Within SD	Av. years	N
Sales	136	2636	14,087	10,362	4672	17.8	22,587
Market value	230	3774	17,654	10,729	10,780	16.4	20,731
SGA expenses	32	404	1431	1016	628	15.7	18,695
R&D expenses	10	120	504	323	259	15.8	18,758
Physical capital	31	802	4798	3444	1768	17.6	22,227
Employees	885	9096	26,407	19,422	9328	17.0	21,544
Internal OC stock	108	1435	5084	3687	2049	15.8	18,606
External OC stock (tech. space)	28,605	32,710	21,669	14,589	16,028	30.0	37,980
External OC stock (market space)	1852	3156	3762	2963	2320	30.0	37,980
Internal R&D stock	49	609	2606	1676	1318	15.8	18,678
External R&D stock (tech. space)	11,203	14,628	11,259	6471	9215	30.0	37,980
External R&D stock (market space)	832	1727	2435	1634	1805	30.0	37,980
Technology fields	29	62.75	88.85	n.a.	n.a.	n.a.	1266
Product markets	3	3.01	1.86	n.a.	n.a.	n.a.	1266

‘Between SD’ illustrates the variation between firms (averaged over time), while ‘Within SD’ illustrates the variation over time, ignoring the between-firm variation. N is the number of observations and ‘Av. years’ indicates the average number of years for which firms are in the dataset. Sales are deflated by the industry price index and SGA expenses are deflated by the implicit GDP price deflator; all price indices are from the Bureau of Economic Analysis. Employees, technology fields and product markets are in numbers; all other variables are in millions of 2005 US dollars. Computation of the external OC stocks R&D stocks, technological fields and number of markets is explained in Sects. 2.3–2.5

SGA selling, general and administrative; R&D research and development; OC organization capital; SD standard deviation

firm’s market share. The market-rival effects, λ_2 and λ_4 , would thus be negative.

2.2 Data sources

We obtained company accounts and stock market data from Datastream and matched these to patent data from Bureau van Dijk’s Orbis database. This paper focuses on manufacturing firms as these are the most intensive investors in intangible assets (Goodridge et al. 2012a). Manufacturing firms are also the most active in taking out patents, which is important for locating firms in technology space and thus for identifying knowledge spillovers of management know-how.

For this reason, we also restrict our sample to manufacturing firms with at least one patent. This leads to data on the patenting activity of 1722 US manufacturing firms, obtained from Orbis. These patent data are matched to company accounts data from Datastream using firm international securities identification number (ISIN) codes as the unique firm identifier. From Datastream we collect information on the number of employees (WC07011), total sales (WC01001), the stock of physical capital (net property, plant, and equipment, WC02501), investment in organization capital (selling, general and administrative expenses, WC01101) R&D expenditure (WC01201), the market value of the company (MVC), preferred stock (WC03451), current assets (WC02201), total debt

(WC03255), total inventories (WC02101) and total intangibles (WC02649) all for the period 1982–2011. Of the 1722 patenting firms from Orbis, 212 were not covered in Datastream and a further 244 firms had missing values for one or more of the company accounts data items. Dropping these firms results in an unbalanced panel of 1266 US manufacturing firms with over 18,000 usable observations. Table 1 provides some basic descriptive statistics on the key variables.

The table shows that the sample covers mostly larger firms and, since the means exceed the medians, the size distribution is skewed. Furthermore, we can follow the firms in our sample for a sizeable number of years, as indicated by the ‘av. years’ column. The (internal) stocks of organization capital and R&D capital (see Sect. 2.3 for measurement details) are large compared to the stock of physical capital, which suggests that these knowledge-based assets could be important for productivity. The potential to learn from organization capital and R&D capital investments by firms that are close in technology space (Sect. 2.4) is large, as indicated by the size of the external stocks. The external stocks of market rivals (Sect. 2.5) are comparatively smaller.

By restricting our sample to firms holding at least one patent, our sample consists of relatively large firms: the median number of employees in Table 1 is 885 versus 581 for a sample that also includes non-patenting firms (see Appendix Table 8). However, as shown in Appendix

Fig. 1 Distribution of firms across industries

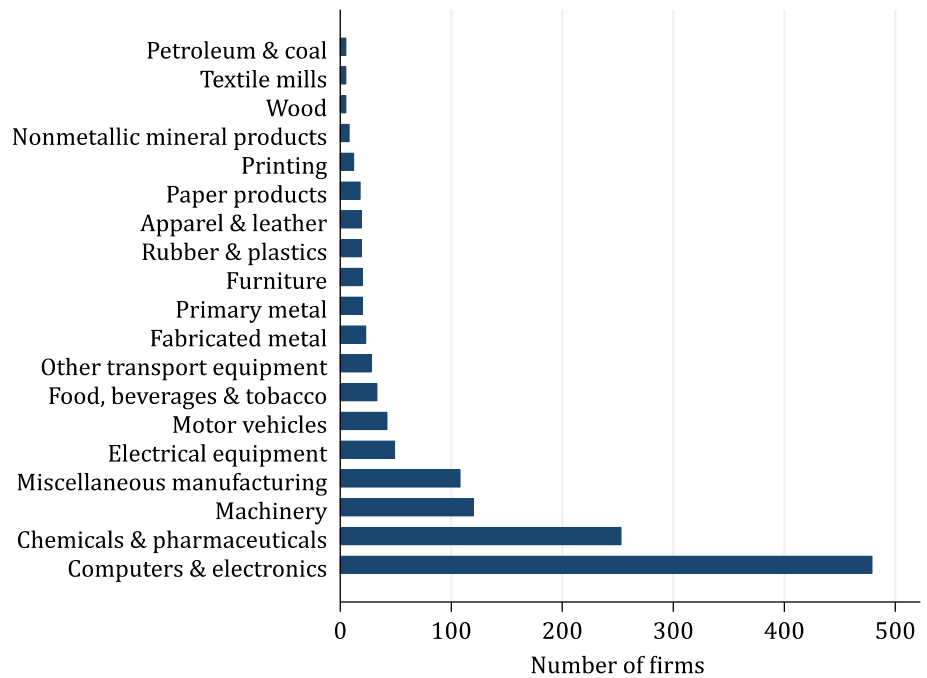


Table 9, the production function estimates (without spillover terms) are comparable to results based on our more restricted sample, suggesting limited scope for sample selection bias.

Figure 1 shows the distribution of firms across 19 broader (2-digit) manufacturing industries. The sample of firms is fairly concentrated in the more high-tech sectors of the economy, such as computers & electronics and chemicals & pharmaceuticals, with the top-five industries accounting for around 80 % of the firms. As shown in Appendix Table 10, our results are not influenced by any of these well-represented industries.

2.3 Measuring organization capital

Investment in organization capital has been measured in a number of ways in the literature. These include business surveys (Black and Lynch 2005), part of the wage bill of managers (Squicciarini and Le Mouel 2012), the residual from a production function (Lev and Radhakrishnan 2005) and selling, general and administrative (SGA) expenses (Tronconi and Vittucci Marzetti 2011; Eisfeldt and Papanikolaou 2013). Given data availability, we opt to use SGA expenses for measuring investment in organization capital. Note that SGA expenses covers many different types of expenditures, and these are typically not broken down in great detail. One of the major items would be advertising expenditure, which represents 9 % of SGA expenses for firms which separately distinguish this item.

Lev and Radhakrishnan (2005) present detailed arguments and examples of how resources allocated to this

expense item can yield improvements in employee incentives, distribution systems, marketing technologies, and a wide range of other organizational structures. Further evidence is from Eisfeldt and Papanikolaou (2013) who find that their measure of organization capital based on SGA expenses correlates highly with the managerial quality scores constructed by Bloom and Van Reenen (2007). This evidence suggests that using SGA expenses to measure organization capital is informative of the quality of management practices across firms.

SGA expenses includes R&D expenditure,⁸ so to focus on organization capital we subtract R&D expenditure to get our measure of investment in organization capital.⁹ To convert this investment flow into an organization capital stock, we apply the perpetual inventory method:

$$G_{i,t} = (1 - \delta)G_{i,t-1} + \frac{SGA_{i,t}}{p_t} \tag{4}$$

where p_t is the implicit GDP deflator from the Bureau of Economic Analysis. To implement the law of motion in Eq. (4), an initial stock and a rate of depreciation must be chosen. Assuming a steady-state relationship from the Solow growth model, the initial stock can be calculated according to:

⁸ At least, according to the definitions employed by Datastream and Compustat.

⁹ Tronconi and Vittucci Marzetti (2011) measure investment as 20 % of this amount to reflect that not all SGA expenses add to organization capital. This is irrelevant from an econometric point of view.

$$G_0 = \frac{SGA_0}{g + \delta} \quad (5)$$

where g denotes the steady-state growth rate of organization capital and δ is the rate at which organization capital become obsolete. According to the aggregate estimates of the INTAN-Invest database compiled by Corrado et al. (2012), organization capital grows at an average rate of 6 % per year, so we use this value for g in Eq. (5).

Organization capital can depreciate over time for a variety of reasons. The existing management practices become obsolete if improvements come along. Organization capital can also erode through work attrition and the adoption of new products or production processes (Hulten and Hao 2008). In the existing empirical works, the assumed rate of depreciation varies between 10 % (Tronconi and Vittucci Marzetti 2011) and 40 % (Corrado et al. 2009). Given that organization capital has two contrasting components: a long-lasting learning-by-doing element which depreciates like R&D; and a short-lived organizational ‘forgetting’ dynamic which depreciates like advertising, a rate in the middle of the range is chosen as our baseline rate; that is, $\delta = 0.25$. The alternative rates of 10 and 40 % will be considered in the robustness analysis. R&D capital is estimated in a similar fashion as organization capital; following BSV, we use a depreciation rate of 15 %.

2.4 Technological proximity

We assume that firms are more likely to learn from the organization capital of firms that are technologically similar. Moreover, we assume that a firm’s patent portfolio defines its technological position and that firms developing or utilizing similar technologies have organized their organizations similarly. As discussed earlier, the diffusion of just-in-time production system and build-to-order supply chain management are two cases in point.

We use the patent data provided in Orbis, which is based on the European Patent Office’s PATSTAT database. This database covers over 80 % of the world’s patents to date and these patents are classified by four-digit international patent classification (IPC) code. This means that even if the firm had been awarded patents from patenting offices in different countries, their patents can be compared. Our sample of 1266 manufacturing firms obtained around half a million patents spanning 612 technology fields, as defined by the first three digits of the IPC code.¹⁰ All patents of a firm are included because it is not possible to select patents

¹⁰ The level of disaggregation of a 3-digit IPC code generates a workable and comparable amount of technology classes to that of BSV. A further breakdown of the classification codes to the fourth digit is not pursued as Henderson et al. (2005) argue that a finer

for a specific time frame, but this is also a helpful feature, as it defines the ‘average’ technological position of a firm, rather than focusing only on activity for a specific period.

Define the vector $T_i = (T_{i1}, T_{i2}, T_{i3}, \dots, T_{i612})$, where $T_{i\tau}$ indicates the number of patents of firm i in technology class τ . The technological proximity between any firm i and j is then defined as the uncentered correlation of patent portfolios, as in Jaffe (1986):

$$P_{ij}^{KH} = T_i T_j' / (T_i T_i')^{\frac{1}{2}} (T_j T_j')^{\frac{1}{2}} \quad (6)$$

The larger the proximity the more effective knowledge of organization capital can diffuse between firms i and j (or vice versa). As indicated in Table 1, the median firm is active in 29 technological fields, providing ample opportunity for learning from other firms in any of these fields. Analogous to BSV, the spillover pool of management know-how available to firm i at time t is calculated as:

$$KH_{i,t} = \sum_{j \neq i} P_{ij}^{KH} \times G_{j,t} \quad (7)$$

2.5 Product market proximity

We also locate firms in product market space, using information on the industries in which firms are active. Datasstream provides up to eight industry codes for each firm at the four-digit standard industrial classification (SIC) level, which means that a firm can be active in up to eight different markets. As shown in Table 1, firms on average report sales activities in 3 different markets out of a total of 569 different four-digit SIC industries.¹¹ Define the vector $S_i = (S_{i1}, S_{i2}, S_{i3}, \dots, S_{i569})$, where S_{ik} indicates whether or not firm i is active in market k . In contrast to BSV, we have no information on the share of sales in each market, but that information was not crucial to their results.¹² Analogous to the technology proximity measure, the market proximity measure for any two firms i and j is calculated as:

$$P_{ij}^{MKT} = S_i S_j' / (S_i S_i')^{\frac{1}{2}} (S_j S_j')^{\frac{1}{2}} \quad (8)$$

The spillover pool of product market for firm i in year t is then constructed as:

Footnote 10 continued
disaggregation would be subject to a greater degree of measurement error.

¹¹ Only few firms (5 %) are active in eight different markets, while many more firms (29 %) are active in just two markets.

¹² For a further comparison, we constructed a market spillover variable for R&D stock like the one used by BSV but based on our information on the number of active markets. For 237 firms, this market spillover variable can be compared to the corresponding BSV variable. The correlation coefficient is high at 0.68, giving confidence that our market spillover measure is comparable to theirs.

Table 2 Firm production function estimates with organization capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	GMM	FE	GMM	FE	GMM	FE	GMM
Physical capital (<i>K</i>)	0.178*** (0.020)	0.151*** (0.038)	0.140*** (0.021)	0.199*** (0.043)	0.182*** (0.021)	0.183*** (0.043)	0.148*** (0.020)	0.191*** (0.042)
Employees (<i>L</i>)	0.712*** (0.029)	0.786*** (0.050)	0.490*** (0.035)	0.581*** (0.067)	0.662*** (0.035)	0.738*** (0.061)	0.495*** (0.035)	0.587*** (0.067)
Organization capital (<i>G</i>)			0.469*** (0.035)	0.222*** (0.047)			0.556*** (0.043)	0.289*** (0.057)
R&D capital (<i>R</i>)					0.117*** (0.027)	0.043 (0.032)	−0.123*** (0.032)	−0.076** (0.038)
Number of observations	20,516	16,970	17,103	13,593	17,169	13,658	17,103	13,593
Number of firms	1238	1200	1149	1077	1150	1078	1149	1077
R ²	0.704	0.700	0.748	0.749	0.728	0.736	0.750	0.750
Returns to scale (H^0 : RTS = 1)	0.890***	0.937**	1.099***	1.001	0.962*	0.965	1.075***	0.990
Hansen J <i>p</i> value		0.313		0.127		0.505		0.234
Weak instrument		118.1		52.33		63.70		39.26

FE: OLS with firm fixed effects; GMM: based on the two-step efficient generalized method of moments (GMM) estimator, using X_{it-2} and X_{it-3} as instruments for X_{it} . Dependent variable in all specifications is real sales and all specifications include firm and year fixed effects, the industry output index and the lag of the industry output index and the industry price index. Robust standard errors, clustered by firm, are shown in parentheses. Returns to scale tests whether the sum of all inputs (*K*, *L* and *G* and *R* where included) is significantly different from one. The Hansen J *p* value is based on a test of overidentifying restrictions, where the null hypothesis is that the instruments are valid. The Weak instrument line gives the Wald F-statistic of the first-stage regression. If this statistic exceeds 11–12 (depending on the specification), the IV bias is less than 5 % of the bias of using OLS, see Stock and Yogo (2005). *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

$$MKT_{i,t} = \sum_{j \neq i} P_{i,j}^{MKT} \times G_{j,t} \tag{9}$$

For the separate identification of knowledge and market rival spillovers we rely on differences in the two proximity measures. The correlation between the proximity metrics in technology and product-market space is 0.196, indicating substantial variation between the two proximity measures.

To illustrate how firms can be located differently in technology and market space, consider the case of Apple, Intel and Dell. These three firms are all close in technology space, with $P_{Apple,Intel}^{KH} = 0.93$, $P_{Apple,Dell}^{KH} = 0.87$ and $P_{Dell,Intel}^{KH} = 0.84$. These proximity measures are high relative to the average $P_{i,j}^{KH}$ of 0.28. However, Apple and Dell are both active in the product market for computers (with Apple also active in other markets) leading to $P_{Apple,Dell}^{MKT} = 0.37$. In contrast, Apple and Dell do not share any product market with Intel, so that $P_{Apple,Intel}^{MKT} = P_{Dell,Intel}^{MKT} = 0$.

3 Results

In this section, we discuss the main empirical findings, with first results of production function estimates without spillovers, followed by the evidence on the presence of spillovers for productivity and market valuation, including the

robustness of that evidence. Finally, we discuss what the spillover results imply in terms of the private and social return to investment in organization capital and discuss our results in relation to GHW and CHJ.

3.1 Production function estimates without spillovers

Table 2 shows production function estimates with firm and year fixed effects and OLS estimation (FE) or general method of moments estimation (GMM). In the GMM estimates, we follow Tronconi and Vittucci Marzetti (2011) and use lagged values of the inputs as instruments; specifically, we use X_{it-2} and X_{it-3} as instruments for X_{it} . The first two columns of Table 2 show production function results with only capital and labor as inputs. Both are highly significant but the sum of the coefficients is significantly smaller than one, indicating decreasing returns to scale. In the next two columns, the stock of organization capital is added to the production function and it enters with a highly significant coefficient. This finding is in line with the earlier firm-level analyses of organization capital and provides further support for considering intangible assets as factors in production alongside tangible capital (Corrado et al. 2005, 2009; Van Ark et al. 2009).

The output elasticity of organization capital is substantial in size and, between 0.222 and 0.469, a similar range as found by Tronconi and Vittucci Marzetti (2011) for their

Table 3 Organization capital spillovers to firm productivity

	(1) FE	(2) GMM	(3) FE	(4) GMM	(5) FE	(6) GMM
OC knowledge spillovers	0.497* (0.254)	0.323 (0.264)			0.149 (0.381)	−0.157 (0.433)
OC market rivals	−0.157*** (0.051)	−0.273*** (0.087)			−0.188*** (0.060)	−0.326*** (0.092)
R&D knowledge spillovers			0.468** (0.200)	0.342* (0.183)	0.353 (0.298)	0.380 (0.323)
R&D market rivals			−0.044 (0.040)	−0.061 (0.047)	0.040 (0.051)	0.064 (0.058)
Physical capital (<i>K</i>)	0.148*** (0.020)	0.194*** (0.042)	0.148*** (0.020)	0.191*** (0.042)	0.148*** (0.020)	0.197*** (0.042)
Employees (<i>L</i>)	0.492*** (0.035)	0.572*** (0.067)	0.494*** (0.035)	0.586*** (0.067)	0.493*** (0.035)	0.576*** (0.067)
Organization capital (<i>G</i>)	0.563*** (0.043)	0.308*** (0.058)	0.555*** (0.043)	0.284*** (0.057)	0.565*** (0.043)	0.311*** (0.059)
R&D capital (<i>R</i>)	−0.125*** (0.032)	−0.077** (0.038)	−0.124*** (0.033)	−0.072* (0.040)	−0.132*** (0.033)	−0.089** (0.041)
Number of observations	17,103	13,593	17,103	13,593	17,103	13,593
Number of firms	1149	1077	1149	1077	1149	1077
R ²	0.750	0.751	0.750	0.750	0.750	0.751
Returns to scale (H^0 : RTS = 1)	1.077***	0.997	1.073***	0.989	1.074***	0.994
Hansen <i>J p</i> value		0.204		0.420		0.409
Weak instrument		32.23		26.76		24.23

The table shows the results from estimating Eq. (2). See notes to Table 2 for details of the production function estimation. The OC knowledge spillovers variable is based on Eq. (7) and the R&D knowledge spillovers variable is defined analogously. The OC market rivals variable is based on Eq. (9) and the R&D market rivals variable is defined analogously

sample of European firms. In columns (5) and (6), we include R&D capital, but exclude organization capital, while in columns (7) and (8), both sets of capital are included. By itself, the R&D capital output elasticity is positive and, in the case of the FE specification, significantly so. The elasticity turns negative when R&D and organization capital are included jointly, but as shown in Appendix Table 9, this negative coefficient is not robust to the set of firms that is included. With these results, a necessary condition for there to be any scope for knowledge spillovers from organization capital has been satisfied: organization capital contributes systematically to own-firm productivity. What is further notable is that the GMM specifications with organization capital show constant returns to scale. This is in contrast with the results of CHJ, whose findings suggest increasing returns to scale. We discuss our findings in relation to theirs in more detail below.

3.2 Spillovers to productivity and market values

Table 3 presents the main productivity spillover results. The first two columns show the results with only spillover terms related to organization capital; columns (3) and (4) mimic the BSV specification about R&D spillovers; and columns (5) and (6) include both sets of spillover variables. The main result is that there is no robust evidence of OC knowledge spillovers on productivity. When also allowing for R&D knowledge spillovers, the point estimates for OC knowledge spillover even turn negative [in column (6)], but remain insignificant. In contrast, the R&D knowledge spillover term is significantly positive by itself, in columns (3) and (4). The R&D knowledge spillover term turns insignificant in columns (5) and (6) mostly because the OC and R&D knowledge spillover terms are highly correlated. Another factor is that our use of robust standard errors, clustered by firm, turns out to be a more conservative

Table 4 Organization capital spillovers to firm market value

	(1) FE	(2) FE-Lag	(3) FE	(4) FE-Lag	(5) FE	(6) FE-Lag
OC knowledge spillovers	−1.529*** (0.586)	−1.764*** (0.572)			−0.934 (1.016)	−1.315 (0.945)
OC market rivals	−0.207* (0.111)	−0.254** (0.103)			0.061 (0.139)	0.063 (0.130)
R&D knowledge spillovers			−1.048* (0.534)	−1.152** (0.516)	−0.459 (0.899)	−0.344 (0.831)
R&D market rivals			−0.308*** (0.085)	−0.336*** (0.081)	−0.336*** (0.104)	−0.367*** (0.100)
OC stock/capital stock	0.328*** (0.050)	0.327*** (0.050)	0.296*** (0.052)	0.291*** (0.052)	0.295*** (0.052)	0.291*** (0.052)
R&D stock/capital stock	0.193*** (0.048)	0.196*** (0.048)	0.228*** (0.050)	0.234*** (0.050)	0.228*** (0.050)	0.234*** (0.050)
Number of observations	14,931	14,931	14,931	14,931	14,931	14,931
Number of firms	1043	1043	1043	1043	1043	1043
R ²	0.302	0.303	0.304	0.306	0.305	0.306

FE: fixed effects; FE-Lag: fixed effects with the spillover variables lagged by one period. Dependent variable in all estimations is Tobin’s Q, defined as the market value of equity plus debt, divided by the stock of fixed capital. A seventh-order polynomial in (OC stock/capital stock) and a fifth-order polynomial in (R&D stock/capital stock) are included, but only the first term is shown for brevity. All specifications include firm and year fixed effects. Robust standard errors, clustered by firm, are shown in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

approach than the Newey–West HAC standard errors used by BSV.¹³

A striking result is the negative OC market rival effect. Taken at face value, this implies that productivity is hurt by rival firm investments in organization capital. As mentioned before, such a ‘face value’ result is hard to reconcile with the industrial organization literature, which considers only a negative market rival effect on firm profitability, not on productivity.¹⁴ One explanation for the negative market-rival effects could be that the inclusion of indexes of industry output and industry prices does not adequately correct for the lack of information on firm-level prices. The market structure in the model of De Loecker (2011) is one of monopolistic competition in a differentiated-product market, but between-firm competition could be fiercer. In that case, the negative coefficients on OC market rivals could reflect a profitability effect, rather than a productivity effect.

Another possibility is that adjustment costs lead to a short-term loss of efficiency as firms need to adjust their inputs to their reduced market share. Given these alternative explanations for the negative coefficients and the lack of a theory-consistent explanation that could help understand why firm productivity would be negatively affected,

we do not take these results as serious evidence of negative productivity spillovers.

We now turn to estimating the market value equation, Eq. (3). Table 4 shows the estimation results using either an OLS firm fixed-effect estimation (FE), or a specification where the spillover variables enter the equation with one lag (FE-Lag). We chose the FE-Lag approach rather than the GMM approach from the production function estimation because the test for overidentifying restrictions showed that lagged values of the explanatory variables were not valid instruments. We thus follow the estimation approach of BSV in using the spillover variables at $t - 1$ rather than at t .

The table shows clear negative market rival effects from R&D, with the coefficients consistently significant and negative in columns (3)–(6). Columns (1) and (2) suggest similar market rival effects from organization capital, but they are not robust to the inclusion of the R&D market rival effect. Similarly, the significantly negative knowledge spillover terms for organization capital and R&D are not robust, as shown in column (5) and (6). It is notable that BSV find significantly positive R&D knowledge spillovers, while we do not. Further checks using the data and program files provided by BSV suggest their R&D knowledge spillovers evidence is not fully robust. For one, their use of Newey-West HAC standard errors is less conservative than our use of robust standard errors, clustered by firm. Second, their data cover 1981–2001, but their estimation sample only uses data for the period 1985–2000. Appendix

¹³ We confirm this using the BSV data, with results shown in Appendix Table 5.

¹⁴ See also Denicolò and Zanchettin (2014).

Table 5 Organization capital spillovers to firm productivity—sensitivity analysis

	Proximity (2–3)	Proximity (1–2)	$\delta = 10 \%$	$\delta = 40 \%$
OC knowledge spillovers	0.323 (0.807)	−1.761 (1.550)	−0.162 (0.467)	−0.232 (0.436)
OC market rivals	−0.165** (0.078)	−0.580*** (0.177)	−0.196** (0.080)	−0.258*** (0.067)
R&D knowledge spillovers	0.020 (0.491)	1.387* (0.733)	0.239 (0.322)	0.446 (0.325)
R&D market rivals	0.027 (0.066)	0.109 (0.097)	0.018 (0.060)	0.040 (0.052)
Physical capital (K)	0.195*** (0.042)	0.183*** (0.042)	0.212*** (0.043)	0.167*** (0.042)
Employees (L)	0.590*** (0.066)	0.598*** (0.066)	0.644*** (0.066)	0.536*** (0.066)
Organization capital (G)	0.284*** (0.056)	0.298*** (0.057)	0.205*** (0.057)	0.356*** (0.059)
R&D capital (R)	−0.076** (0.038)	−0.091** (0.039)	−0.048 (0.043)	−0.071* (0.037)
Number of observations	13,593	13,593	13,593	13,593
Number of firms	1077	1077	1077	1077
R ²	0.750	0.751	0.744	0.756
Returns to scale (H ⁰ : RTS = 1)	0.993	0.987	1.013	0.989
Hansen J p value	0.594	0.309	0.0981	0.769
Weak instrument	20.66	26.14	21.40	21.59

See notes to Table 2 on the estimation of the production function and to Table 3 on the spillover terms. For brevity, only GMM specifications are shown, comparable to column (6) of Table 3 for the baseline model. In the baseline model, patents are categorized into 3-digit patent categories and 4-digit industry categories for determining proximity in technology space [Eq. (6)] and in market space [Eq. (8)]. Column ‘Proximity (2–3)’ uses 2-digit patent categories and 3-digit industry categories; column ‘Proximity (1–2)’ uses 1-digit patent categories and 2-digit industry categories. In the baseline model, organization capital is assumed to depreciate at a geometric rate δ of 25 %. The column ‘ $\delta = 10 \%$ ’ assumes a 10 % rate and the column ‘ $\delta = 40 \%$ ’ assumes a 40 % rate

Table 12 shows that the evidence for R&D knowledge spillovers is less convincing when using the more conservative standard errors and the full sample period.

3.3 Sensitivity analysis

In Tables 5 and 6, we present regression results that vary the measurement of proximity in technology and market space and of organization capital. We first aim to test whether our results depend on the definition of proximity in the technology and product market space. In the baseline model, a firm’s position in technology space is determined based on the 3-digit IPC classification of its patent portfolio and its position in market space is determined based on the 4-digit SIC industry codes the firm is active in. We consider two alternatives: (1) IPC code at 2-digit with SIC code at 3-digit [denoted ‘Proximity (2–3)’] and (2) IPC code at 1-digit with SIC code at 2-digit [denoted ‘Proximity (1–2)’]. For brevity, we only report the GMM specifications in Table 5, comparable to column (6) of

Table 3; in Table 6 we only report the fixed effect lagged (FE-Lag) specifications, comparable to column (6) of Table 4. Results for the fixed effect specifications are available upon request. We also vary the assumed depreciation rate for organization capital. The 25 % depreciation of the baseline model is an average of commonly-used depreciation rates in the literature, but we also consider a much lower rate of 10 % and a much higher rate of 40 %.

The most important result from Tables 5 and 6 is that there are no significant knowledge spillovers from organization capital to productivity (Table 5) or market values (Table 6), regardless of the proximity definitions or the assumed depreciation rate. When assuming a lower depreciation rate, the output elasticity of organization capital is smaller, because the stocks of organization capital are larger. Despite this variation, the null hypothesis of constant returns to scale also cannot be rejected under the two alternative depreciation rates. Further sensitivity analysis is in Appendix Table 10, which shows that excluding a single industry at a time does not affect the results.

Table 6 Organization capital spillovers to firm market value—sensitivity analysis

	Proximity (2–3)	Proximity (1–2)	$\delta = 10 \%$	$\delta = 40 \%$
OC knowledge spillovers	−1.168 (1.429)	2.077 (2.058)	−1.965* (1.107)	−0.761 (0.853)
OC market rivals	0.148 (0.150)	−0.257 (0.241)	0.047 (0.146)	0.109 (0.122)
R&D knowledge spillovers	−0.657 (1.059)	−1.954* (1.084)	−0.241 (0.845)	−0.746 (0.817)
R&D market rivals	−0.335*** (0.112)	−0.222 (0.208)	−0.400*** (0.099)	−0.421*** (0.095)
OC stock/capital stock	0.307*** (0.051)	0.314*** (0.051)	0.263*** (0.042)	0.284*** (0.041)
R&D stock/capital stock	0.216*** (0.049)	0.206*** (0.049)	0.412*** (0.032)	0.424*** (0.031)
Observations	14,931	14,931	14,931	14,931
Number of firms	1043	1043	1043	1043
R ²	0.304	0.301	0.307	0.306

See notes to Table 4 on the estimation of the market value equation and notes to Table 5 for an explanation of the column headings. For brevity, only the FE-Lag specifications are shown, comparable to column (6) of Table 4 for the baseline model

3.4 Private and social returns to organization capital

With our results, we can gauge the marginal social and private returns to investment in organization capital, again following BSV. Consider, first, the output elasticity $\gamma_1 = \rho \times (G/Y)$, where ρ is the marginal productivity of organization capital G . If one assumes a constant marginal product γ_1 and a constant discount rate r along with an infinite planning horizon, then ρ can be given the economic interpretation of a marginal gross internal rate of return.¹⁵ In BSV, the marginal social return (MSR) to organization capital of firm i is defined as the increase in aggregate output generated by a marginal increase in firm i 's organization capital stock:

$$MSR = (Y/G)(\gamma_1 + \phi_1) \tag{10}$$

where γ_1 and ϕ_1 are the coefficients from estimating Eq. (2) as given in Table 3. The MSR can be interpreted as the marginal product of a firm's organization capital contributed: (1) directly from firm's own organization capital stock (γ_1) and (2) indirectly from the external stock of management knowledge, ϕ_1 . The marginal private return (MPR) is defined as the increase in firm i 's output generated by a marginal increase in its own stock of organization capital:

$$MPR = (Y/G)(\gamma_1 - \sigma\lambda_2) \tag{11}$$

Own organization capital increases a firm's own sales, thus γ_1 is part of the MPR. Also included is λ_2 since the firm's own organization capital has a business-stealing effect on its product market rivals, as given in the market value equation. This business-stealing effect increases the private incentive to invest in organization capital by redistributing output between firms. The business-stealing effect on market values will generally consist of a (negative) impact on rival firms' prices and output levels. The share of the overall effect that falls on output is represented by parameter σ and, in line with BSV, is set at $\frac{1}{2}$. More in general, the size of σ will depend on the precise model of product market competition.

As our estimates of the different parameters (γ_1, ϕ_1 and λ_2) vary notably between specifications and because the spillover parameters ϕ_1 and λ_2 are often not statistically significant, it is most helpful to report 95-percent confidence intervals (estimated using the delta method) alongside the point estimates. In Table 7, we report the *MSR* and *MPR* estimates based on parameters from two specifications, namely from column 2 of Tables 3 and 4—which give relatively optimistic estimates of organization capital knowledge spillovers—and column 6 of Tables 3 and 4—which give relatively pessimistic estimates. As the table shows, the MPR of investment in organization capital is significantly positive. Column 2 of Table 4 showed a significantly negative business-stealing effect, which results in a higher MPR; column 6 of Table 4 showed a positive but insignificant business-stealing effect, which results in a lower MPR and a wider confidence interval.

¹⁵ For a detailed derivation and discussion, see Hall et al. (2010).

Table 7 The marginal social and private return to investment in organization capital

	Column 2		Column 6	
MSR	0.636	[0.073–1.200]	0.155	[−0.710–1.026]
MPR	0.438	[0.337–0.540]	0.282	[0.153–0.411]

The marginal social return (MSR) and marginal private return (MPR) from investment in organization capital are estimated using Eqs. (10) and (11) and the parameter estimates as given in Tables 3 and 4 from the indicated columns. Reported in square brackets are the 95-percent confidence intervals, which are estimated using the delta method

The MSR estimates show much more uncertainty. Based on the estimates in column 2 of Table 3, the point estimate of the MSR is higher than the MPR, but the confidence interval is very wide. In column 6 of Table 3, the point estimate of knowledge spillovers from organization capital is negative, leading to a lower MSR and an even wider confidence interval that even includes zero. So despite the clearly positive private benefits to investment in organization capital, the social benefits are much more uncertain and could well be less than the private return.

3.5 Discussion

As mentioned in the introduction, we are not the first to analyze potential spillover effects from organization capital or knowledge-based/intangible assets more in general. GHW find knowledge spillovers from UK industry stocks of ‘economic competencies’, which overlaps substantially with our measure of organization capital.¹⁶ CHJ find knowledge spillovers from non-R&D intangible assets using market sector capital stocks for the US and European economies. Investment in non-R&D intangible consists in equal parts of investment in organization capital (as we define it) and other intangible investments.¹⁷

The difference in asset coverage could account for the difference in findings, especially in comparison with the CHJ results: their knowledge spillovers could stem from many other assets than from organization capital. But a first question would be whether their findings on knowledge spillovers could refer to knowledge spillovers from organization capital given the lack of evidence for such spillovers in this paper. GHW find some evidence of positive external effects, with industries learning about the organizational capital practices of their suppliers, but no support for the movements of workers between industries as a channel for external effects. GHW also find negative internal stock effects, which could be the same negative

market-rival effect we find: investments in organization capital by other firms in the industry adversely affect the investing firm.

There is a larger gap in findings with CHJ, who find evidence of positive productivity spillovers based on economy-wide data. If firm-level returns to scale are constant—as they are in our data—the findings of CHJ would point to between-firm spillovers. If such between-firm spillovers exist at the economy-wide level, this would imply that our analysis is not looking at the right channels through which knowledge about intangible capital ‘spills over’ between firms. Indeed, it could be that knowledge diffuses through the supply chain, through worker flows or in other ways that we cannot readily measure.

At its most limited, the contribution of our paper is thus to show that there is no evidence to support the notion that firms with more similar technologies (as reflected in their patent portfolio) learn from each other’s organization capital. However, a corollary of this contribution is that any ‘true’ between-firm spillover channel cannot be positively correlated with the similarity of firm patent portfolios. Furthermore, such a true between-firm spillover channel also cannot be positively correlated with within-firm organization capital, because if it were, we would have found (robust) evidence of increasing returns to scale in our basic production function estimates. Such a lack of correlation would be at odds with the literature on learning (e.g. Cohen and Levinthal 1989), which argues that firms invest in R&D (in part) with the aim of learning about R&D done by other firms. Given that the hypothesized spillovers from organization capital are also thought of as knowledge spillovers, a greater spillover potential should lead to greater within-firm investments in organization capital. So, given our findings, it is not straightforward to hypothesize how knowledge spillovers from organization capital would operate.

An alternative explanation would be that we measure organization capital with greater error than CHJ or GHW. Such measurement error would make it harder for us to find significant evidence of knowledge spillovers. GHW and CHJ can certainly analyze more precisely-delineated measures of intangible capital than we are able to. Our investment measure, SGA, includes spending on advertising and managerial compensation—both of which GHW

¹⁶ ‘Economic competencies’ consists for 80 % of our measure of organization capital and for 20 % of investment of worker training.

¹⁷ Specifically, investment in software, new architectural and engineering designs, development of new financial products, entertainment, artistic and literary originals, mineral exploration and worker training.

and CHJ also consider as investment in intangible assets—but also spending that is not related to intangible capital formation, such as rents. That said, the CHJ and GHW numbers are also imperfect measurements of ‘true’ organization capital. It could be that having more and better-paid managers leads to the accumulation of more efficient organizational structures, but this is more of a presumption than a result. It is, for example, not known if firms that invest more in organization capital (according to the CHJ/GHW measures) adopt more performance-enhancing management practices, as measured by Bloom and van Reenen (2007). There is a positive correlation, though, between the quality of management practices and SGA-based measures of organization capital, as shown by Einfeldt and Papanikolaou (2013). This suggests that the measurement error in our SGA-based measure is not so large as to drown out a useful signal.

Furthermore it is not a given that measurement error would play a more substantial role in our firm-level setting given that we have many more observations (18,000 versus 100) and can more extensively control for confounding factors and employ econometrically appealing methods. Furthermore, we can focus on firms in manufacturing, to which the production function framework can be more easily applied than to some of the services industries in the data of GHW, for which e.g. output prices are much harder to measure. Finally, GHW and CHJ both adjust their measure of output to include the estimated investment in intangibles. While this is logical within the framework of the System of National Accounts—investment goods have to be produced first—our focus on real sales as the output indicator has a much clearer interpretation: it is the sales to customers that brings in revenues—and thus can lead to profits—while the imputed output value of intangible capital investment is nothing more than an accounting element to balance the (national accountant’s) books.

Given these considerations, it is hard to see how organization capital could be a source of substantial knowledge spillovers. Especially the evidence from CHJ can most easily be interpreted as evidence of knowledge spillovers from ‘non-R&D, non-organization capital’ intangible assets. The evidence of GHW was more mixed to begin with, with both negative and positive effects. We would thus argue that, first, our results place limits on where we can hope to find any knowledge spillovers from organization capital; and second, that caution is in order when interpreting evidence of knowledge spillovers from intangible capital based on aggregate evidence.

4 Conclusions

This paper is the first to present a firm-level analysis of knowledge spillovers from investment in organization capital. With traditional tangible capital, aggregate productivity benefits are simply a summation of firm benefits, but when the asset is intangible—as is the case with organization capital—there may be spillovers across firms that drive a wedge between the private and social returns of investment.

Our analysis is based on a sample of 1266 US manufacturing firms. We locate each firm in technology space, to capture potential knowledge spillovers of organizational capital between technologically similar firms; and in product market space to capture negative ‘market-stealing’ spillovers from competitors. We find no significant knowledge spillovers and only limited evidence for market-stealing effects on the market value of firms.

This lack of evidence stands in contrast to recent studies by GHW and CHJ that do find evidence for spillovers from intangible assets based on more aggregate data. We have argued that, at the very least, our findings limit the scope of where positive knowledge spillovers from organization capital can be found. More broadly our paper suggests that knowledge about organization capital does not readily spill over between firms. This can be best understood if information about organization capital is tacit, firm-specific and idiosyncratic. Seen in that light, it seems more sensible to interpret the evidence of GHW and CHJ as evidence in favor of knowledge spillovers from intangible assets other than organization capital. Either way, the lack of supportive firm-level evidence on knowledge spillovers from organization capital suggests caution is in order when looking for intangible assets as a potential accelerator of productivity growth.

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Appendix

See Tables 8, 9, 10, 11 and 12.

Table 8 Descriptive statistics for a sample including non-patenting firms

	Median	Mean	SD	Between SD	Within SD	Av. years	N
Sales	87	2150	12,484	8548	4119	14.6	29,228
Market value	174	3170	15,912	8976	9661	13.9	25,756
SGA expenses	22	331	1279	810	558	12.4	23,839
R&D expenses	6	95	449	257	230	12.4	23,950
Physical capital	20	653	4241	2768	1561	14.3	28,688
Employees	581	7538	23,806	15,739	8344	13.6	27,173
Internal OC stock	74	1172	4533	2927	1815	12.4	23,839
Internal R&D stock	28	481	2315	1326	1164	12.4	23,950

‘Between SD’ illustrates the variation between firms (averaged over time), while ‘Within SD’ illustrates the variation over time, ignoring the between-firm variation. Sales are deflated by the industry price index and SGA expenses are deflated by the implicit GDP price deflator; all price indices are from the Bureau of Economic Analysis. Employees are in numbers; all other variables are in millions of 2005 US dollars

SGA selling, general and administrative; R&D research and development, OC organization capital; SD standard deviation

Table 9 Production function estimates for a sample including non-patenting firms

	(1)	(2)	(3)	(4)
Physical capital (<i>K</i>)	0.206*** (0.042)	0.239*** (0.046)	0.231*** (0.046)	0.251*** (0.050)
Employees (<i>L</i>)	0.702*** (0.056)	0.492*** (0.070)	0.651*** (0.062)	0.476*** (0.073)
Organization capital (<i>G</i>)		0.246*** (0.046)		0.226*** (0.055)
R&D capital (<i>R</i>)			0.072** (0.032)	0.025 (0.032)
Number of observations	18,171	13,994	14,058	13,994
Number of firms	1432	1232	1233	1232
R ²	0.664	0.731	0.72	0.729
Returns to scale (H^0 : RTS = 1)	0.908***	0.977	0.954*	0.979
Hansen J <i>p</i> value	0.48	0.103	0.588	0.178
Weak instrument	82.46	44.92	43.45	34.31

All results are estimated using on the two-step efficient generalized method of moments (GMM) estimator, using X_{it-2} and X_{it-3} as instruments for X_{it} . Dependent variable in all estimations is real sales and all specifications include firm and year fixed effects, the industry output index and the lag of the industry output index and the industry price index. Robust standard errors, clustered by firm, are shown in parentheses. Returns to scale tests whether the sum of all inputs (*K*, *L* and *G* and *R* where included) is significantly different from one. The Hansen J *p* value is based on a test of overidentifying restrictions, where the null hypothesis is that the instruments are valid. The Weak instrument line gives the Wald F-statistic of the first-stage regression. If this statistic exceeds 11–12 (depending on the specification), the IV bias is less than 5 % of the bias of using OLS, see Stock and Yogo (2005). *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 10 Sensitivity of spillover estimate to removing single industries

Excluding industry	(1) Chemicals	(2) Computers	(3) Electrical	(4) Machinery	(5) Miscellaneous
OC knowledge spillovers	−0.526 (0.446)	0.278 (0.501)	−0.174 (0.431)	−0.204 (0.600)	−0.304 (0.424)
OC market rivals	−0.215** (0.0907)	−0.380*** (0.121)	−0.298*** (0.0919)	−0.330*** (0.103)	−0.314*** (0.0915)

Table 10 continued

Excluding industry	(1) Chemicals	(2) Computers	(3) Electrical	(4) Machinery	(5) Miscellaneous
R&D knowledge spillovers	0.759** (0.316)	-0.0614 (0.393)	0.382 (0.331)	0.462 -0.406	0.373 (0.325)
R&D market rivals	0.0632 (0.0590)	0.0909 (0.0684)	0.0479 (0.0593)	0.0558 (0.0653)	0.0542 (0.0591)
Physical capital (<i>K</i>)	0.160*** (0.0401)	0.259*** -0.0635	0.173*** -0.0417	0.196*** (0.0439)	0.210*** (0.0458)
Employees (<i>L</i>)	0.587*** (0.0666)	0.542*** -0.0969	0.609*** -0.0649	0.579*** (0.0698)	0.563*** -0.0707
Organization capital (<i>G</i>)	0.308*** (0.0639)	0.296*** (0.0784)	0.307*** (0.0540)	0.314*** -0.0627	0.281*** -0.0571
R&D capital (<i>R</i>)	-0.0991** -0.0418	-0.0936* (0.0519)	-0.0884** -0.0417	-0.0918** -0.0447	-0.0594 -0.0406
Number of observations	11,303	7821	13,100	12,195	12,533
Number of firms	871	626	1038	973	981
R ²	0.823	0.564	0.756	0.751	0.755
Returns to scale (H^0 : RTS = 1)	0.956*	1.003	1.001	0.997	0.995
<i>p</i> value	0.0652	0.943	0.969	0.904	0.841
Hansen <i>J p</i> value	0.335	0.409	0.533	0.403	0.456
Weak instrument	24.01	12.55	21.51	22.96	28.82

The table shows the results from estimating Eq. (2), excluding a single industry at a time. Only the largest five industries are considered in this table, given that these (together) represent 80 % of firms in the sample. The OC knowledge spillovers variable is based on Eq. (7) and the R&D knowledge spillovers variable is defined analogously. The OC market rivals variable is based on Eq. (9) and the R&D market rivals variable is defined analogously

Table 11 Production function estimates including materials inputs

	(1)	(2)	(3)	(4)
Physical capital (<i>K</i>)	0.140*** (0.013)	0.160*** (0.037)	0.152*** (0.037)	0.154*** (0.037)
Employees (<i>L</i>)	0.667*** (0.020)	0.557*** (0.060)	0.660*** (0.058)	0.549*** (0.059)
Materials (<i>M</i>)	0.090*** (0.012)	0.066* (0.036)	0.061* (0.036)	0.056 (0.036)
Organization capital (<i>G</i>)		0.173*** (0.046)		0.238*** (0.052)
R&D capital (<i>R</i>)			0.047 (0.031)	-0.058* (0.035)
Number of observations	11,831	9755	9790	9755
Number of firms	924	831	832	831
R ²	0.814	0.832	0.822	0.834
Returns to scale (H^0 : RTS = 1)	0.897***	0.957*	0.859***	0.884***
Hansen <i>J p</i> value	0.00,105	0.154	0.338	0.224
Weak instrument	412.9	19.18	21.25	15.78

All results are estimated using on the two-step efficient generalized method of moments (GMM) estimator, using X_{it-2} and X_{it-3} as instruments for X_{it} . See notes to Appendix Table 9 for further details. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 12 Sensitivity of BSV results to sampling cut-off and standard errors

	Production function			Market value equation		
	NW 1985–2000	NW 1981–2001	Clustered	NW 1985–2000	NW 1981–2001	Clustered
R&D knowledge spillovers	0.191*** (0.046)	0.241*** (0.039)	0.241*** (0.068)	0.381*** (0.113)	0.208** (0.090)	0.208 (0.148)
R&D market rivals	−0.005 (0.011)	0.007 (0.010)	0.007 (0.017)	−0.083*** (0.032)	−0.023 (0.026)	−0.023 (0.048)
Physical capital (K)	0.154*** (0.012)	0.168*** (0.013)	0.168*** (0.021)			
Employees (L)	0.636*** (0.015)	0.644*** (0.013)	0.644*** (0.021)			
R&D capital (R)	0.043*** (0.007)	0.038*** (0.006)	0.038*** (0.011)			
R&D stock/capital stock				0.806*** (0.197)	0.325* (0.174)	0.325 (0.248)
Observations	9935	12,471	12,471	9944	12,542	12,542

The columns ‘NW 1985–2000’ replicate the results from BSV, with production function estimates from Table 5 [column (2)] and market value equation estimates from Table 3 [column (2)] and, like BSV, using Newey–West HAC standard errors. The columns ‘NW 1981–2001’ correct the sampling cut-off error to cover all available data from BSV with Newey–West HAC standard errors. The columns ‘Clustered’ replace the Newey–West HAC standard errors by robust standard errors, clustered by firm

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