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Does local knowledge spillover matter for firm productivity? The role of financial access and corporate governance

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ABSTRACT

Global productivity growth has either stagnated or declined, despite continued technological innovations with the rise of knowledge-intensive intangibles that arise from the growth of knowledge stock (R&D activities). Understanding the root causes of this paradox in the context of growing economies requires an investigation of whether local knowledge diffusion can explain firm-level productivity differences, including key constraining factors like sources of financing or corporate governance structure. Using financial data of 7970 Indian firms over a 20-year period and clustering firms across industries, we assess the impact of R&D stock that is external to the firm through estimating both within (intra) and between (inter) industry spillovers. We find that both R&D and non-R&D-performing firms benefit from 'between industry' spillovers. We further show that firms with better access to finance achieve higher productivity, not only through their own R&D capital stock but also via both types of industry-level knowledge spillover. We allow for the two key sources of international spillovers namely import intensity and FDI. While import-intensive firms experience lower productivity, FDI mitigates this adverse productivity effect across knowledge-intensive exporting firms. The paper concludes that financially unconstrained firms and firms with greater corporate board connectedness derive positive industry-level spillover effects, reflecting intra- and inter-industry as domestic spillover or local value-chain effect in the literature on technological innovation.

1. Introduction

Technological innovation is the prime engine of economic modernization that can enable a higher level of development. Since the cross-country analysis of international technology spillovers by Coe and Helpman (1995), this topic has attracted considerable interest in understanding the theoretical and empirical determinants of Total Factor Productivity (TFP). It is now well established that domestic TFP not only depends on a country's own R&D capital but also on the R&D spillovers from embodied and disembodied foreign knowledge pools.[1] In the same vein, knowledge spillovers are equally crucial at the industry-level and/or firm-level productivity growth.

India is one of the rapidly growing emerging economies. However, India's low innovation rate and low productivity growth remain one of the concerns of Indian policymakers, with recent policy priorities for greater innovation (see Ghosh and Parab, 2021). Hence, understanding the factors driving firm-level productivity in India is timely and important. Furthermore, although the linkages between R&D spillover and productivity growth have been established in relation to advanced economies, the same cannot be said vis-à-vis emerging economies. Studies analysing the cases of emerging economies are limited. The few exceptions include Lee et al. (2016) and Singh (2004), who analyse knowledge spillover across Korean firms, while Nemlioglu and Mallick (2021) study the innovation and performance of Turkish firms. In this paper, we aim to study the impact of domestic (local) inter- and intra-industry knowledge spillovers in driving firm-level productivity in India. In so doing, we also examine the roles of Indian firms' financial access and corporate governance structure in explaining the impact of knowledge spillover on firm-level productivity.

Firm productivity could benefit from reduced financial constraints

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[1] See Luintel and Khan (2004, 2017), Keller and Yeaple (2009), and Bournakis et al. (2018) for a comprehensive review of the literature on international technology spillover.

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(Feenstra et al., 2014). Financially less constrained firms tend to be more innovative by exploiting their own R&D stock as well as the know-how spillovers from domestic inter- and intra-industry knowledge pools. Lee et al. (2016) conduct a comparative study of knowledge spillovers emanating from arm's length firms (market) versus those emanating from firms in the same business group (network) in Korea by clearly separating their respective knowledge pools. They find intra- and inter-sector knowledge spillovers to be significant; however, the magnitude of spillovers from business networks dominated those from other industries. Although the extent of Korean network organizations may not be prevalent in other emerging countries in general, knowledge spillover can still occur to firms across industries with a greater degree of inter-industry transactions (also see Singh, 2004).

In the case of Indian firms, Raut (1995) shows the presence of R&D spillovers in a sample of private manufacturing firms over the period 1975–1986. Kathuria (2002) reports that only those domestic firms that invested in R&D benefitted from foreign knowledge spillover during the 1990s. However, Kathuria (2010) reports that domestic firms are more productive in many industries than foreign firms, precluding the possibility of spillovers to firms across all sectors. Using a sample of manufacturing firms over the period 2001–2010, Kanwar and Singh (2018), on the other hand, show that knowledge spillovers are highly significant in explaining patent counts. However, they do not consider different types (inter- and intra-industry) of spillovers, which we aim to capture in this study by employing both the disembodied and embodied inter- and intra-industry domestic knowledge pools. In so doing, we also assess the roles of imported inputs, import intensity, and FDI in shaping the net effect of local spillover on firm-level productivity. Besides, firms in emerging markets tend to be more financially constrained, and their corporate governance mechanism could be weaker, both of which could inhibit knowledge spillovers. Hence, we also examine these issues in the context of Indian firms, as the key novelties being explored in this paper.

The absorptive capacity is extremely important to realise knowledge spillover (see Aghion and Jaravel, 2015) which primarily depends on firms' knowledge stocks and innovative activities. Knowledge as a public good may not carry any cost when it is publicly available within a country. Still, in an international context, such technological (knowledge) externalities can emanate only when a local firm undertakes transactions with their overseas partners through imports or FDI flows. A recent meta-analysis by Ugur et al. (2020) confirms that R&D spillovers are indeed an important source of productivity gains. Within this context, we aim to analyse productivity gains at firm-level within a single country because the evidence on domestic R&D spillover remains somewhat ambiguous (see Bournakis et al., 2018) along with its underlying conduits. Put differently, in contrast to international spillovers, there is limited consensus on the role of domestic or national spillovers. In this paper, we aim to explore the role of domestic spillovers, including intra- and inter-industry linkages and their potential conduits of knowledge transmissions across Indian firms. Besides, the low pace of India's innovation in the past decades requires us to assess the innovative capacity of Indian firms in the wake of economic liberalisation since the early 1990s, which allows us to understand the key constraints underlying the productivity performance of non-financial Indian firms in sustaining their pace of high growth.

Grossman and Helpman (1991) pioneered the role of a single R&D sector that innovates and uses each innovation to produce a new variety, suggesting that innovation takes place only in the country with the larger stock of knowledge capital; however, different knowledge endowments within a single country can spillover across industries, influencing their productivity, on which there is limited evidence in the literature. Studies such as Hall and Oriani (2006) and Bloom and Van Reenen (2010) show that productivity differences across countries were attributed to the stock of R&D capital that produces technical change. Using data from five OECD countries (US, UK, Japan, France and Germany), O'Mahony and Vecchi (2009) estimated the relationship between R&D and productivity across high-tech and low-tech industries. They found that firms within knowledge-creating or skill-intensive industry benefit from 2 to 5 % higher productivity growth.

Assessing the relationship between TFP and international technological spillovers in Asian countries, Singh (2001) reports that R&D at the industry level is crucial while confirming the relative importance of international technological spillovers compared to domestic R&D stock. As external spillover is already a long-established source of know-how at cross-country and industry levels (Luintel and Khan, 2004; Bournakis et al., 2018), in this paper, we focus on national spillover at firm levels along with different sources of firm financing and governance mechanisms in improving their performance.

According to Lee and Malerba (2017), in relation to innovation, the late-comer economies must be prepared to open for catch-up without wasting any opportunity. They argue that these countries should be ready to develop sector-specific capabilities by supporting the actors, networks, and institutions, which in turn will lead to innovation and growth. In this context, R&D stock at the firm level is critical for industrial innovation, which also requires considerable absorptive capacity to move towards the high end of the global value chain. Using Indian firm-level annual data covering 7970 companies from 1995 to 2015, we find that 'between-industry' spillovers are significant at the firm level. This finding contrasts with the insignificant domestic spillover at the aggregate level in industry-level studies for OECD countries (see, for example, Bournakis et al., 2018). We also find that within-industry spillover per se is not statistically significant in certain cases; nonetheless, one dominant result is that less credit-constrained firms tend to benefit from both types of knowledge spillovers. Therefore, policymakers can focus on the sectors that are more R&D intensive or that rely more on access to credit to absorb knowledge spillover. Furthermore, our findings can help policymakers to identify and focus on those sectors that need timely support to become global leaders. Our findings would also help policymakers to design regulations to promote credit policies for firms to ease their financial constraints. Moreover, the findings regarding better-connected boards, along with knowledge spillover, would also aid policymakers in promoting an efficient corporate governance mechanism, bringing about an environment of well-connected corporate boards for better dissemination of knowledge across industries.

The remaining parts of the paper are structured as follows. Section 2 presents the literature review and hypotheses development, Section 3 examines the data and methodology, Section 4 presents the empirical strategy, and Section 5 discusses the results and the robustness checks. Finally, Section 6 concludes the paper.

2. Literature review and hypothesis development

Relatively stagnant productivity growth in recent years has been an issue of concern which raises questions about the role of R&D spillover nationally across industries that might be driving productivity-enhancing investment and innovation and thereby impacting firm productivity growth. Innovation is often classified as product or process innovation, but TFP improvement could capture the effect of both types of innovation. R&D spillovers refer to leakages or positive externalities that a firm cannot appropriate out of its R&D activities, and such spillovers flow to its competitors in the same industry, reducing the production costs of other firms. To capture the existence of knowledge spillovers, several studies have shown that trade and FDI are the key channels for knowledge transmission (Ang and Madsen, 2013; Luintel and Khan, 2017). R&D investments by firms play a key role in improving firm productivity, as it is already a stylised fact that there are social returns to innovation (see Griffith et al. (2003, 2004); Bourlès et al. (2013); Bloom et al. (2013); and Bournakis and Mallick (2018) on the role of R&D in productivity catch-up models).

Theoretically, to achieve higher productivity, firms must learn, create, adopt, and commercialise knowledge and technologies through internal R&D activities or external sources (Ning et al., 2016). Thus, firms with higher absorptive capacity on the back of greater knowledge stock could realise the importance of knowledge spillover and thereby adopt any new technology from the external environment (whether within a country or from overseas). Through their enhanced absorptive capacity, the R&D-performing (also non-R&D-performing) firms can increase their performance via increased technology spillovers from intangible assets available within their own industry or outside their industry, and therefore turn external R&D stock into productivity gains (see Bournakis et al., 2018; and Singh, 2004, for industry-level evidence for OECD and Korean industries respectively). However, the evidence on the presence of domestic spillover remains mixed that could depend on the flow of within-country knowledge, given the public goods nature of knowledge within a national boundary. Neves and Sequeira (2018) find that the spillover effect tends to be greater when the estimation of knowledge production accounts for foreign inputs, and it tends to be lower when the estimation includes only rich economies, and the pool of knowledge is not the patent stock. Studies that estimate production function look at the elasticity of firm sales with respect to R&D capital stock or estimate rates of return on R&D capital. In this paper, we estimate firm-level TFP and model the effect of R&D on TFP.

On the other hand, there is a growing literature about the existence of learning effects from exporting (see Melitz (2003) for a theoretical exposition on heterogeneous-firm trade literature). Many studies have found evidence on both "self-selection into exporting" (productive firms becoming exporters) and on "learning by exporting" (exporters are able to increase their productivity) (see, for example, Mallick and Yang (2013)). This international dimension has already been explored in this literature showing international knowledge transmission via trade and FDI channels (Bournakis et al., 2018); nevertheless, there is limited evidence on domestic spillover, as knowledge flow within a country might be considered as more publicly available, and hence those firms which do not invest in R&D could benefit from knowledge-intensive firms in the same industry or between industries. Thus, we separate firms into R&D-performing and non-performing firms to uncover such heterogeneity in the sense that knowledge-intensive (or more productive who could also be engaged in exporting) firms try to upgrade their product quality through accumulating R&D stock.

In other words, it is known that higher quality standards in international markets relative to domestic markets could provide greater incentives for local firms to upgrade their production technologies (Verhoogen, 2008), suggesting that these knowledge-intensive firms produce higher quality products and, therefore, could make non-knowledge intensive firms to gain domestic intra- or inter-industry knowledge spillover. Melitz's (2003) model of firm heterogeneity in productivity could be linked to such heterogeneity in product innovation and knowledge-intensity of firms. Considering the positive externalities generated by R&D activities, over the last two decades, R&D spillovers have been studied extensively as one of the channels of technological progress. Therefore, the stock of R&D and its spillovers can have a favourable effect on firm performance, which leads us to the following hypotheses.

H1. Stock of own R&D has a positive impact on firm performance.

H1a. Intra- and/or Inter-industry knowledge spillover positively impacts firm performance.

2.1. Impact of financial constraints on R&D decisions and firm performance

Using a cross-country/cross-industry setup, Rajan and Zingales (1998) show that industries that rely more on external financing grow slowly in countries with poorly developed financial markets. This evidence suggests that financial constraints matter more in low-income countries such as India. Since financial constraints inhibit innovation and productivity (see Mallick and Yang, 2011), firms that get access to external finance would be more innovative and, thus, more productive. In other words, firms that have better access to external finance could potentially finance their R&D activities better and, therefore, could do better in terms of their productivity improvement. Firms require costly capital to acquire available knowledge capital. Therefore, a lack of financial capital can limit the knowledge capital and potential know-how spillover, even if they are available in the same country. Innovative activities could get a boost when a firm can have better access to bank borrowing. Studies on financial constraints suggest that financially constrained firms tend to invest in R&D due to being locked into R&D activities because of previous commitments and agreements (see Archibugi et al., 2013). Different sources of financing can impact firm performance differently, and hence more financially constrained firms may rely on a greater level of financial leverage. Any negative effect of such financial leverage can be mitigated via a higher level of firm innovation as an important dimension of firm performance.

Across different types of financing (bank loans, bonds, and equities), most firms still rely on bank financing. The role of financing is critical for innovative firms to be more productive. Using a rich firm-level data set, Dabla-Norris et al. (2012) find that innovation is crucial for firm productivity in less-developed countries, but the role of country-level financial sector development influencing the innovation-productivity link is weak, although the innovation effect on productivity is more significant for high-tech firms. However, debt financing at the firm-level can reveal a more accurate picture and therefore boost firm performance and innovation. Campello (2006) finds that moderate debt-taking is associated with sales gains, whereas high indebtedness leads to product market underperformance. Using firm-level data from 47 countries, Mallick and Yang (2011) provide evidence that while retained earnings and equities positively affect productivity, bank and non-bank loans tend to impact productivity negatively. Such a negative effect of debt financing can be mitigated via innovation, as in Nemlioglu and Mallick (2017), using R&D flow information. To better capture this linkage between financing and innovation in our context, we investigate the joint impact of bank financing with R&D spillovers via interaction terms, as this has rarely been investigated in previous studies as a channel in exploring the effect of domestic knowledge spillover.

H2. For firms with greater financing access, Intra- or Inter-industry R&D spillover positively impacts firm performance.

2.2. Impact of corporate connectedness on R&D decisions and firm performance

Aside from financing, corporate board diversity through several governance characteristics could reflect better managerial practices and therefore explain the mixed effect of technology spillover on productivity differences across firms at the national level. Apart from some common corporate governance indicators such as the size of the corporate board, CEO duality, and the share of women on board, in this paper, we aim to explore an unexplored area: the role of boardroom networks on the relation between innovation and productivity.

A corporate board with heterogeneous directors could possess a wealth of information on innovation, market trends, and regulatory changes. This information can flow across the boardroom via the boardroom networks. Therefore, a well-connected corporate board has access to a pool of information that provides a comparative advantage to managers, and thus it is vital for strategic decision-making (Mizruchi, 1996; Mol, 2001). In other words, a firm with well-connected board directors can overcome information challenges, and thereby facilitate managers to make the optimal decision in allocating factors of production, undertaking R&D projects, and thus becoming more productive.

The empirical evidence on boardroom networks and firm performance is mixed. While Fich and Shivdasani (2006) and Hauser (2018) find a negative association between the boardroom network and firm performance, Larcker et al. (2013) and Field et al. (2013) find a positive association. Taking large US firms, Fich and Shivdasani (2006) show that a well-connected, but busy board is associated with weak corporate governance and lower firm performance. Besides busy boards, weak corporate governance culture may also arise due to the board of directors overlooking the activities of the largest controlling shareholders when they have tight control in the firm, which in turn can lower productivity (Boubaker et al., 2021). In a recent study, taking Finnish and Swedish firms, Afzali and Kettunen (2022) find that boardroom centrality, measured by directorship interlocks, positively impacts the future performance of private firms. They also find that private firms with boardroom centrality have better employee productivity. Given the mixed evidence on the role of corporate connectedness on firm performance, we are interested in the following hypothesis:

H3. Firms with more connected boards enhance the knowledge stock-productivity relationship.

3. Data measurements and model specification

We use firm-level annual data from the Prowess database published by the Centre for Monitoring Indian Economy (CMIE) from 1995 to 2015,[2] covering data of >7970 non-financial and manufacturing companies in India. Most of the companies incorporated in the database are listed on stock exchanges. To scrutinise differences in productivity and innovation capability across firms, we classify firms on the sectoral basis of R&D intensity, trade orientation (exporting versus non-exporting), and firm size.[3] The literature that models the role of R&D on firm level productivity essentially takes production function approach which we follow. To compute firm-level TFP, a standard firm-level production function is specified and estimated:

$$y_{it} = \phi_i + \lambda_t + \alpha k_{it} + \beta l_{it} + \gamma m_{it} + \varepsilon_{it} \tag{1}$$

$i = 1,2, \ldots,N$; number of firms; $t = 1, \ldots.T$ time dimension.

where: y_{it} = firm's total sales, k_{it}= firm's physical capital stock; m_{it}= firm's intermediate inputs and l_{it}= firm-level labour (wages and salaries). All variables are in natural logs; ϕ_i and $\lambda_t$are the firm specific fixed effects and time effects, which we include in all estimations. We calculate the physical capital stock of each firm in the sample through firm's real gross fixed investment using the perpetual inventory method.

The measurement of TFP is undertaken based on Levinsohn and Petrin's (2003) method which uses intermediate inputs as an instrument (to deal with the endogeneity of inputs in the production function) that may respond more smoothly to unobserved productivity shocks.[4] In Eq. (1), the residual term (ε_{it}) is the firm level TFP. We model the firm's TFP and R&D capital stock relationship as follows:

$$ln\varepsilon_{it} = \theta_i + \varphi_t + \beta_d lnS^r_{it} + \beta_i lnS^{intra}_{it} + \beta_f lnS^{inter}_{it} + e_{it} \tag{2}$$

where θ_i and φ_t are firm and time fixed effects; S^r_{it} denotes each firm's own R&D capital stock (in-house R&D capital stock of each firm). We calculate each firm's knowledge stock from its real R&D expenditure flows by using 15 % and 25 % depreciation rates separately for each firm. S^{intra}_{it} denotes the intra-industry R&D capital stock relevant to the i^{th} firm, i.e., the total R&D stock of all firms in the industry where this i^{th} firm belongs to minus the i^{th} firm's R&D stock; S^{inter}_{it}denotes the inter-industry R&D stock relevant to the i^{th} firm, i.e., the total R&D stock of all industries in the sample minus the R&D stock of the industry where i^{th} firm belongs to (S^{intra}_{it}).

3.1. Computation of firm's own knowledge pool and spillover pools

The i^{th} sample firm's own (self-accumulated) knowledge stock or knowledge pool at time t $\left(S^r_{it}\right)$ is calculated from the i^{th} firm's annual flow of real R&D expenditure $\left(R_{exp,i,t}\right)$ employing the well-known perpetual inventory method which is widely used in the literature. This requires, inter alia, firm's own initial stock of knowledge,S_{i0}, which is computed as:$S_{i0} = \frac{\overline{R}_i}{g_i+\delta}$, where δ denotes the rate of depreciation of firm's knowledge stock; g_i is the average annual growth rate of $R_{exp,i,t}$ (real R&D spending growth rate of 5 %) over the sample period. The initial value of firm's real R&D expenditure, $\overline{R}_i$, is calculated as the mean value of the first five years' $R_{exp,i,t}$ in the sample. Once the initial knowledge stock is generated, the subsequent calculation of knowledge stock is straightforward accumulation overtime: $S_{it} = (1-\delta)S_{i,t-1} + R_{exp,i,t}$.

We calculate two alternative measures of firm-level own knowledge pool based on the depreciation rates (δ) of R&D stock common for all firms at 15 and 25 %.[5] The use of perpetual inventory method is often called into question due to its assumptions regarding the average life of capital stocks, depreciation rates as well as taxes on capital assets, which are not straightforward. Nevertheless, this approach is universally used in the literature.

Besides a firm's own R&D stock, we also compute both the intra-industry (between firms within the same industry) and the inter-industry (between firms across different industry sectors) knowledge pools. Knowledge spillovers take place when firm 'i' derives economic benefit from the R&D activity of firm 'j' without the former sharing the cost. We focus on two potential sources of intra-national knowledge spillovers, viz., the *intra-industry* and the *inter-industry* knowledge spillovers for each of the i^{th} firm in our sample. The i^{th} firm could reap the know-how benefits from the knowledge pool accumulated by the other firms of its own industry through their R&D activities. This is classed as the *intra-industry* knowledge spillovers. Likewise, the i^{th} firm could also benefit from the knowledge pool of firms that are outside of its own industries. This is classed as the *inter-industry* knowledge spillovers. To model the nature and the extent of these potential spillover externalities, we need measures of firm specific *intra-industry* and *inter-industry* knowledge stocks. Knowledge spillovers emanate in two forms, namely, the embodied and the disembodied (Luintel and Khan, 2017) which shape the computation of knowledge pool as the sources of spillovers. In the literature of international knowledge spillovers, cross-country transactions such as total imports, capital goods imports, exports, FDI, geographical and technological proximity, and the mobility of inventors between countries feature as the main conduits of knowledge transmissions. However, within national boundaries, knowledge diffusions take the forms of *intra-industry* and *inter-industry* knowledge spillovers across domestic firms; therefore, transaction data across these firms involving intermediate and capital goods are viewed as the main conduits of embodied knowledge diffusion.

Unfortunately, to the best of our knowledge, there is no detailed data on India's intra- and inter-industry firm-level transactions. However, we have some information on cross-industry transactions. Specifically, we have data on the cross-section of 45 industries ($j = 1 \ldots 45$) covering their intra industry purchases/sales of intermediate goods. Utilising these industry-level purchases of intermediate goods, we construct bilateral weights W_{jk}, which is the proportion of intermediate goods purchased by industry k from industry j (Timmer et al., 2015). We generate a time-varying weighting matrix $w_{jkt(45\times45)}$, and set the diagonal elements of

[2] Since input-output (I—O) table data is available until 2013, which we use in the embodied spillover estimate at industry-level, we restricted our overall sample until 2015, and impose 2013's I—O values for 2014 and 2015.

[3] Baumann and Kritikos (2016) find little difference in productivity gain from R&D activities by small or large firms in Germany.

[4] For the problems associated with measuring firm-level productivity, see Ackerberg, Caves and Frazer (2015), and Doraszelski and Jaumandreu (2013). Also see Bournakis and Mallick (2018) for an overview of all the methods of measuring firm-level productivity.

[5] Both depreciation rates provide very similar results. Therefore, for brevity, we report the results based on 25 % depreciation rate only.

this matrix to 0 (i.e., weight is 0 when $j = k$). The intra-industry weights (w_{jkt}) are simply the k^{th} industry's purchase of intermediate goods from industry j expressed as the ratio of k^{th} industry's total intermediate goods purchase in year t. The intra-industry embodied knowledge spillover for the i^{th} firm can be written as follows:

$$S_{it}^{Eintra} = \sum_{j=1,j\neq k}^{N-k} w_{jkt}{}^{*} S_{jt}$$

where S_{it}^{Eintra} is the embodied intra-industry spillover pool for the i^{th} firm. Likewise, the embodied inter-industry spillover pools are calculated for each of the firms in the sample equivalently by using the same weights. However, in a world of highly competitive pressures and technology rivalry, researchers have cast doubt on the bona fide of embodied knowledge transmissions across firms. For example, Branstetter (1998, p. 523) states, “At the firm level, the most intense knowledge spillovers may be those which take place between direct competitors who buy nothing from one another”. Likewise, it is the fact of life that firms maintain ‘secrecy’ to protect profits from inventions and they engage into patent blocking activities by taking out patents early to pre-empt rivals from patenting (Cohen et al., 2000). Hence, it is believed that the tacit knowledge and high-concept innovations are diffused beyond any conduits (Kloosterman, 2008). Hence, we also compute firm level disembodied inter- and intra-industry knowledge pools. The disembodied knowledge pool is essentially the unweighted sum of the knowledge stock of other firms in the sample, devoid of any conduits. The *intra-industry* disembodied knowledge spillover pool for the i^{th} firm is:

$$S_{it}^{\mathrm{Dintra}} = \sum_{j=1;j\neq i}^{N-i} S_{jt}$$

where S_{it}^{Dintra} is the disembodied intra-industry knowledge pool for the i^{th} firm in the sample which is just the un-weighted sum of the R&D knowledge stocks of all the firms in industry I, where the i^{th} firm belongs to but exclusive of it ($S_{jt}; j = 1,2,\ldots,N-1; t = 1,2,\ldots,T; j \neq i$). Clearly, we calculate separate *intra-industry* spillover pool germane to each of the firms in our sample. Likewise, the relevant disembodied *inter-industry* spillover pool, $S_{i,t}^{Dinter}$, for the i^{th} firm is computed as:

$$S_{it}^{Dinter} = \sum_{\substack{K=1\\K\neq I}}^{M-1} \sum_{l=1}^{L_K} S_{Klt}$$

where there are a total of M industries (K = 1…,I, …,M), inclusive of industry I, in the sample and for simplicity each industry has a total of L firms. S_{Klt} is the firm specific stock of knowledge in the K^{th} industry. The *inter-industry* spillover pool relevant to the i^{th} firm is just the sum of all industry level R&D knowledge stock excluding that of the industry I where the firm i belongs.

Our conditioning model of firm level productivity and R&D is:

$$lnTFP_{it} = \alpha_i + \varphi_t + \lambda lnS_{it} + \phi lnS_{i,t}^{intra} + \beta lnS_{i,t}^{inter} + \theta' X_{it} + e_{it} \tag{3}$$

($i = 1, \ldots$,N; and $t = 1, \ldots$,T).

where subscripts i and t denote the cross-sectional and time series dimensions of sample firms, respectively; $TFP_{i,t}$ denotes the total factor productivity of each of our sample firms which we estimate following Levinson and Pertin (2003) as discussed above. The covariates S_{it}, S_{it}^{intra} and S_{it}^{inter} are respectively the i^{th} firm's own accumulated knowledge stock, and the *intra-* and *inter-industry* knowledge spillover pools specific to this firm. In the estimations, we use two separate measures (embodied and disembodied) of intra- and inter-industry spillover pools. Following the mainstream literature, we specify a contemporaneous relationship between firm's productivity and knowledge pools (see Coe and Helpman, 1995; Luintel and Khan, 2004). X_{it} is the vector of other conditioning covariates that are anticipated to affect firm-level productivity. Specifically, the latter includes firm characteristics: sample firms' size and age, the composition of firms' Board of Directors, firms' CEO characteristics, and firms' access to bank finance. We model these additional conditioning variables in a structured way.

Specification (3) is a panel data model where α_i captures the time-invariant but firm-specific fixed effects and φ_t captures the firm-invariant time effects. The parameter λ is the point estimate of the elasticity of firms' own (in-house) knowledge stock. A priori λ is expected to be significantly positive, implying that firms' own knowledge stock contributes to firm productivity. Firms' in-house knowledge stock is also an important factor in determining their knowledge absorption capacity (Cohen and Levinthal, 1989; Ramani et al., 2008). A significantly positive ϕ implies the existence of *intra-industry* knowledge spillovers across firms, which significantly facilitates their productivity. Likewise, a significantly positive β implies positive *inter-industry* knowledge spillovers across firms that are conducive to firm-level productivity. However, the parameters (ϕ andβ) could also be negative and significant, indicating intense inter-firm rivalry where the accumulation of knowledge by competing firms is productivity taxing. This is because knowledge spillovers could be materialised in two ways: ‘pecuniary’ spillovers and ‘pure’ knowledge spillovers (Jaffe, 1986; Branstetter, 2001; Luintel and Khan, 2017). When firm A improves its creativity through reverse engineering of a superior technology of firm B, then that creates ‘pure’ knowledge spillover from firm B to A, which is unequivocally productivity enhancing for firm A. However, when firm B is unable to appropriate the full benefits of its innovation — due to host of factors inhibiting perfect price discrimination — and some benefits leak to firm A, then that creates ‘pecuniary’ spillover. Unfortunately, we cannot observe and isolate ‘pure’ knowledge spillovers. Parameters β and ϕ capture the combined effects of these two spillovers to a typical firm. Therefore, if competitive pressures and technology rivalry are fierce between firms, then the net spillover effect, and hence the signs of the spillover parameters, could be negative. Put differently, any theft of know-how by reverse engineering or any other means by a fierce competitor could be productivity debilitating. On the other hand, insignificant ϕ and β implies absence of *intra-* and *inter-industry* knowledge spillovers across the sample firms. The parameter vector,θ, is associated with the vector of covariates, $X_{i,t}$, capturing firm-specific characteristics and other conditioning variables discussed above.

Our specification is consistent with both the micro and the macro empirical literature on R&D-productivity relationship. Micro literature typically models firm-level productivity as a function of the firm's own accumulated knowledge and other firms' accumulated knowledge, measured as spillover pools (e.g., Jaffe, 1986). The measurements of spillover pools could be *intranational* as well as *international* (Branstetter, 2001) or *intrasectoral* and *intersectoral* across different technology fields (Ramani et al., 2008). Because of the data limitations, we have measured two types of knowledge spillover pools at the *intranational* level: the *intra-industry* and the *inter-industry* spillover pools. In the international context, total factor productivity and R&D relationship is modelled as a function of the country's own accumulated knowledge stock and foreign knowledge stocks capturing the embodied and disembodied knowledge spillovers (Luintel and Khan, 2017; Bournakis et al., 2018). Our specification (3) captures these basic arguments of both micro and macro literature on the R&D-productivity relationship, and we extend it by other conditioning variables representing firm characteristics, management characteristics and access to bank finance.

4. Empirical method and strategy

We take a structured approach to investigate the R&D-productivity relationships across different clusters of Indian firms. Our analysis does not confine to the full sample of firms alone. Specifically, we segregate the full sample of firms into the R&D-performing and R&D-non-

Table 1
Variables, definition, and source.

Variables	Definition	Source
Total factor productivity	TFP is measured using levpet methods in Stata	Own calculation
Log(R&D capital stock)	Logarithm of R&D capital stock is measured using 25 % depreciation rate	Own calculation
Log(Intra-industry R&D capital stock)	Logarithm of intra-industry R&D capital stock is measured as the Intra-industry R&D capital stock relevant to the i^{th} firm. That is the total R&D stock of all firms in the industry where thei^{th} firm belongs to minus the i^{th} firm's R&D stock	Own calculation
Log(Inter-industry R&D capital stock)	Logarithm of inter-industry R&D capital stock is measured as the Inter-industry R&D capital stock relevant to the i^{th} firm. That is the total R&D stock of all industries in the sample minus the intra-industry R&D stock of the i^{th} firm	Own calculation
Firm size	Logarithm of total assets of firm	CMIE Prowess
Bank loan	Ratio of total bank borrowing over sales	CMIE Prowess
Imp	It measures the imported raw materials consumed as the share of total raw materials consumption: it captures the share of imported raw materials to total raw materials consumed during the year.	CMIE Prowess
Firm age	Logarithm of firm age	CMIE Prowess
Log(Board size)	Logarithm of the number of directors in the board in a year	CMIE Prowess
CEO duality	1 if CEO is also Chairman or else 0	CMIE Prowess
Share of women on board	Share of women in the board of directorates in a year	CMIE Prowess
Eigenvector centrality	It represents that a board is well-connected if its direct contacts are also well-connected. It is measured based on the direct links of its well-connectedness.	Own calculation

performing firms. We further segregate the sample of R&D-performing firms into: (i) labour intensive, firms having higher than the median value of wages and salaries to the value-added ratio in the sample; (ii) capital intensive, firms with higher than the median value of total investment to the value-added ratio; (iii) R&D intensive, firms with higher than the median value of R&D expenses to total sales ratio; and (iv) export intensive, firms with higher than the median value of exports to sales ratio in the sample. Thus, we separately analyse seven clusters of firms (full sample, separate samples of R&D-performing and R&D non-performing firms, and the four different intensity-based clusters). The R&D non-performing sample is modelled to assess whether the firms that do not undertake R&D activities also benefit from other firms' R&D via spillovers.

We use fixed effects models with robust standard errors for our benchmark estimation. As R&D stock can be endogenous depending on firm absorptive capacities, namely the level of access to financing, we use dynamic panel estimation along with interaction terms. We have estimated the effects of intra- and inter-industry R&D spillover considering both embodied and disembodied knowledge spillovers. Our regression models also control for an array of firm-specific characteristics. Specifically, we include the logarithm of total assets to control for firm size. We include the ratio of total bank borrowing over sales to capture the effect of access to bank financing on productivity. We also include firm age (in logs) as one of the firm characteristics.

We collect information on the number of board directors for each year to account for scale effects through company board size (in logs) (Helmers et al., 2017). To see the effects of CEO-Chairman duality, we create a dummy variable that takes 1 if the CEO is also the firm's Chairman. To account for gender diversity in the corporate board, and

Table 2
Summary statistics.
This table reports the Summary statistics of the Embodied sample of all R&D-performing and Non-R&D-performing firms separately. *TFP* is the Total Factor Productivity, measured as proposed by Petrin et al. (2004). *Log(R&D capital stock)*, *Log(Intra-industry R&D capital stock)*, and *Log(Inter-industry R&D capital stock)* are R&D knowledge stocks as defined in Table 1. *Firm size* is the Logarithm of total assets while *Firm age* is the Logarithm of the age of firms. *Imp* is the imported raw materials consumed as the share of total raw materials consumption. *Bank loan* is the ratio of total bank borrowing over sales. *Log(Board size)* is the Logarithm of the number of directors in the board in a year. *CEO duality* is a dummy variable that takes the value of 1 if CEO is also the Chairman or else 0. *Share of women on board* is the share of women directors on board in a year. *Eigenvector centrality* measures the connectedness of a corporate board if its direct contracts are also well-connected. It is measured based on the direct links of its well-connectedness.

	Mean	Median	Std. deviation	Min	Max	N
Panel A: R&D-performing firms						
TFP	1.146	1.043	0.876	−1.772	4.889	11,595
Log(R&D capital stock)	3.397	2.968	0.991	2.720	9.686	11,595
Log(Intra-industry R&D capital stock)	3.092	3.127	1.724	−5.954	8.123	11,595
Log(Inter-industry R&D capital stock)	7.742	8.176	1.826	0	9.925	11,595
Firm size	7.575	7.507	1.639	2.394	11.115	11,595
Firm age	3.441	3.434	0.589	1.099	4.883	11,595
Bank loan	0.32	0.181	0.468	0	3.305	11,595
Imported raw materials consumed (Imp)	0.299	0.22	0.302	0	1.34	11,595
Log(Board size)	2.192	2.197	0.396	0	3.555	9316
CEO duality	0.036	0	0.185	0	1	9316
Share of women on board	0.03	0	0.068	0	1	9316
Eigenvector centrality	0.018	0.004	0.047	0	1	9316
Panel B: Non-R&D-performing firms						
TFP	1.327	1.167	1.142	−1.772	5.349	38,226
Log(R&D capital stock)						
Log(Intra-industry R&D capital stock)	1.39	1.571	1.916	−6.524	8.132	38,226
Log(Inter-industry R&D capital stock)	7.735	8.219	1.942	0	9.939	38,226
Firm size	6.01	5.883	1.659	2.394	11.115	38,226
Firm age	3.019	2.996	0.619	0	4.963	38,226
Bank loan	0.587	0.203	1.664	0	14.238	38,226
Imported raw materials consumed (Imp)	0.162	0	0.279	0	1.199	38,226
Log(Board size)	1.857	1.946	0.463	0	3.664	24,407
CEO duality	0.041	0	0.198	0	1	24,407
Share of women on board	0.039	0	0.092	0	1	24,407
Eigenvector centrality	0.006	0.001	0.018	0	0.563	24,407

whether it has any effect on productivity, we construct a time-varying variable that represents the share of women on the board of directorates.

4.1. Construction of boardroom network

The Prowess database provides information on the directors sitting on the boards of each firm. As the listing of these directors is unique for

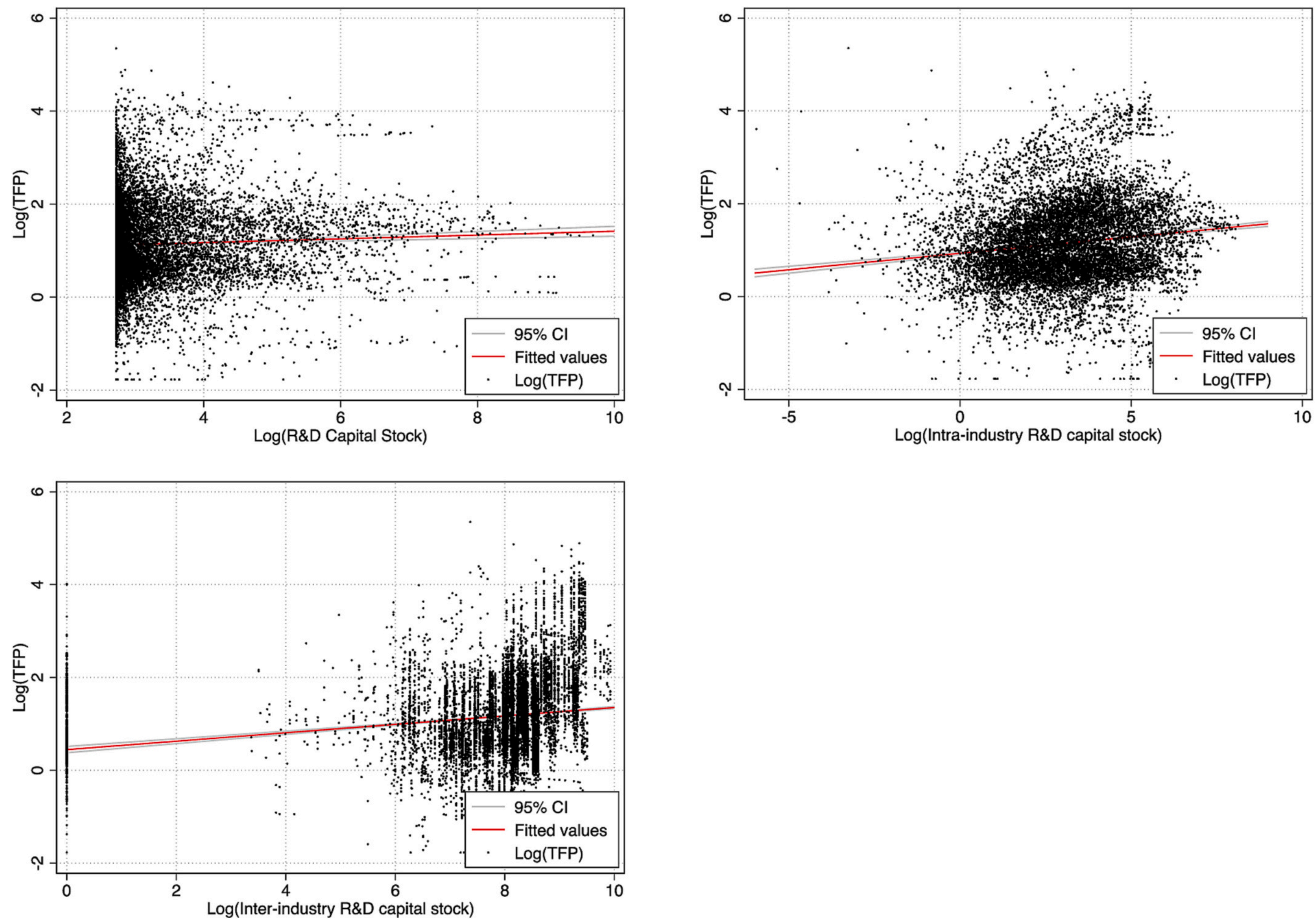

Fig. 1. Scatter plots of R&D knowledge spillovers and productivity.

each time period, we are able to construct a non-directed and unweighted boardroom network that is formed by shared directorates (see Larcker et al., 2013). If two firms share at least one board member (referred to as vertex), we consider these firms to be linked and have shared directorates. As shared directorates can be the conduit for channelling information or resources, we consider that the stronger the shared directorates, the more they can influence the innovative decision-making of firms, and hence their productivity.

The influence of the shared directorates depends on how well they relate to each other. Since a corporate board's connectedness relies on how much its direct links are well-connected, Larcker et al. (2013) argue that *Eigenvector centrality* captures the notions of power and prestige. It represents that a board is well-connected if the direct contacts of its directorates are also well-connected. The Eigenvector centrality is well-suited for the Indian context as the most powerful and prestigious boards might have a special advantage in obtaining information and resources that help them innovate and grow. We measure the *Eigenvector centrality* based on the direct links of its directorates' well-connectedness, which can be described as *Eigenvector Centrality* $= \frac{1}{\lambda}\sum_{l=1}^{1} A_{il} C_E(i)$, where λ is a constant, A_{il} represents the adjacent vertices between i and its l neighbours, and $C_E(i)$ measures the sum of all adjacent vertices' eigenvector centrality scores (See Goergen et al. (2019) for an elaborate discussion on eigenvector centrality).

Table 1 outlines all the relevant data series. Table 2 reports data summary statistics for two categories (R&D-performing and R&D non-performing) of firms of the embodied sample (descriptive statistics of the disembodied sample are reported in Appendix Table A1). Overall, there are 11,595 firm-year observations for the period 1995–2015. The average TFP (log) is 1.146, with a standard deviation of 0.876 for the R&D-performing firms. The average bank loan-to-sale ratio is 0.32, with a standard deviation of 0.47, indicating a substantial variation in accessing bank credit among Indian firms. The average age of firms in the sample is 36.76 years, with a board size of 9.62 members.

5. Discussion of findings

We estimate the samples of (i) all R&D-performing firms and (ii) non-R&D-performing firms. All R&D-performing and non-performing firms exhaust the full sample of firms. Thus, we have parameters of production function relating to the full R&D-performing and non-R&D-performing firms with their different sub-samples categorised based on labour-, capital-, R&D-, and export-intensive activities. We use fixed effects models with robust standard errors for each sample/sub-sample. As R&D intensity can be endogenous, which can vary depending on the level of access to financing, we also use the GMM estimator along with interaction terms between R&D intensity and the type of financing as a robustness check. We have panel data spanning 20 years. We estimate the model specification (3) in log levels and examine the effects of intra- and inter-industry knowledge spillover in explaining the firm-level productivity in India. As stated above, we employ both the disembodied and embodied measures of these knowledge pools, in turn.

First, we present the baseline regression results estimated by OLS while controlling for time and firm fixed effects. Before discussing the regression results, we graphically illustrate the scatterplots of the embodied pool of knowledge spillovers and TFP in Fig. 1. Plots show that as R&D capital stock increases, productivity also increases.

Table 3
The effect of R&D capital stock on total factor productivity.
The dependent variable is the Total Factor Productivity (TFP) as proposed by Petrin et al. (2004). This table presents the results of fixed effects estimation involving embodied knowledge pools and R&D-performing firms. Both the year and the firm fixed effects are maintained in all estimations. Column 1 includes all R&D-performing firms in the sample. However, we categorize these firms as labour-, capital-, R&D-, and export-intensive and estimate them separately. Results are reported for these sub-panels in columns 2 through 5. *p*-Values [.] are calculated using the heteroskedasticity-robust standard errors. Control variables include firm size, firm age, bank loan ratio, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms	Labour	Capital	R&D	Export
	1	2	3	4	5
Log(R&D capital stock)	0.004	0.038***	0.033***	0.008	−0.003
	[0.007]	[0.012]	[0.011]	[0.010]	[0.010]
Log(Intra-industry R&D capital stock)	−0.043***	0.002	0.035	−0.019	−0.002
	[0.015]	[0.030]	[0.029]	[0.016]	[0.015]
Log(Inter-industry R&D capital stock)	0.004***	0.002	0.006***	0.001	0.002
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
Firm size	0.169***	0.130***	0.138***	0.139***	0.111***
	[0.014]	[0.026]	[0.024]	[0.018]	[0.021]
Firm age	−0.272***	−0.325***	−0.326***	−0.308***	−0.200***
	[0.039]	[0.061]	[0.053]	[0.056]	[0.063]
Bank loan (BL)	−0.229***	−0.191***	−0.160***	−0.267***	−0.191***
	[0.015]	[0.020]	[0.017]	[0.021]	[0.019]
Imported raw materials consumed (Imp)	−0.004	−0.004	0.006	−0.066**	0.003
	[0.018]	[0.030]	[0.024]	[0.026]	[0.024]
Constant	1.129***	1.318***	1.105***	1.321***	1.489***
	[0.149]	[0.236]	[0.220]	[0.204]	[0.238]
Observations	11,595	5465	5624	5643	4847
Adjusted R-squared	0.938	0.941	0.951	0.927	0.952
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	1572	948	911	913	767

Table 4
The effects of knowledge spillovers on total factor productivity of non-R&D-performing firms.
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Embodied sample of the Non-R&D-performing firms. Column 1 takes all firms in the sample. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 2, 3, 4, and 5, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms	Labour	Capital	Export
	1	2	3	4
Log(Intra-industry R&D capital stock)	−0.019**	0.097***	0.083***	−0.051***
	[0.009]	[0.010]	[0.011]	[0.017]
Log(Inter-industry R&D capital stock)	0.003**	0.004***	0.005***	0.004**
	[0.001]	[0.001]	[0.002]	[0.002]
Firm size	0.181***	0.053***	0.081***	0.205***
	[0.010]	[0.012]	[0.013]	[0.017]
Firm age	−0.169***	−0.202***	−0.103***	−0.075
	[0.028]	[0.040]	[0.040]	[0.048]
Bank loan (BL)	−0.121***	−0.072***	−0.081***	−0.144***
	[0.005]	[0.005]	[0.004]	[0.014]
Imported raw materials consumed (Imp)	0.009	0.062***	0.033	0.025
	[0.018]	[0.023]	[0.022]	[0.024]
Constant	1.113***	1.115***	1.279***	1.170***
	[0.149]	[0.180]	[0.202]	[0.169]
Observations	38,226	17,981	18,193	8805
Adjusted R-squared	0.899	0.886	0.883	0.949
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of firms	5974	3534	3465	1593

Likewise, the higher the intra- and inter-industry knowledge spillovers, the higher the productivity levels of Indian firms. Table 3 presents the results using the embodied pool of knowledge spillovers. For all R&D-performing firms, column 1, results show that the coefficient of firms' own R&D stock is positive but insignificant. However, the productivity effects of intra- and inter-industry knowledge spillovers appear significant. Specifically, the productivity of sample Indian firms does not appear to benefit from the intra-industry knowledge spillovers, but they do significantly benefit from inter-industry knowledge spillovers. These results indicate that cross-industry know-how spillovers generate positive externalities for firm-level productivity in India; however, the intra-industry spillover parameter is significantly negative, indicating fierce competition between these firms. These results are anticipated and theoretically consistent because fierce competition for market share is expected between firms operating in the same industry, while competition between firms belonging to different industries tends to be muted.

The results in column 2 show that the productivity effect of firms' R&D stock is positive and significant at the 1 % level across labour-intensive Indian firms. However, the intra- and inter-industry knowledge spillovers appear completely insignificant. In column 3, we report results pertaining to capital-intensive firms, where firms' own knowledge stock is positive and significant, and so are the inter-industry knowledge spillovers. However, intra-industry knowledge spillovers are insignificant, implying no statistically significant positive externality across firms in the same industry. A comparison of columns 2 and 3 indicates that R&D-performing capital-intensive firms benefit from inter-industry knowledge spillovers, not labour-intensive ones. Results of columns 4 and 5 show that R&D-intensive and export-intensive Indian firms do not appear to benefit from their own knowledge stocks or inter- and intra-industry knowledge spillovers from the embodied knowledge pools. Both spillover parameters appear insignificant. The insignificance of firms' own knowledge stock in explaining firm-level productivity for these two categories of firms is puzzling and hard to explain.

However, the R&D-productivity relationship appears more promising across the disembodied measure of knowledge pools. Results are reported in Appendix Table A2. The panel of all R&D-performing firms appears to benefit from the intra- and inter-industry knowledge spillovers vis-à-vis their productivity, although firms' own R&D stock appears insignificant in explaining their productivity. Interestingly, the significantly negative intra-industry spillover parameter of embodied knowledge pool, reported earlier, turns out to be positive and significant for all firms with the disembodied measure. Further, with disembodied

Table 5

The effect of R&D capital stock on total factor productivity: the role of access to bank loans.

The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Embodied sample of the R&D-performing firms. Columns 1–3 take all firms in the sample. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 4–6, 7–9, 10–12, and 13–15, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms			Labour			Capital			R&D			Export		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Log(R&D capital stock)	−0.029***	−0.002	0.004	−0.008	0.028**	0.037***	−0.007	0.026**	0.032***	0.003	0.008	0.008	−0.022**	−0.007	−0.003
	[0.008]	[0.007]	[0.007]	[0.013]	[0.012]	[0.012]	[0.011]	[0.010]	[0.011]	[0.012]	[0.010]	[0.010]	[0.011]	[0.009]	[0.010]
Log(Intra-industry R&D capital stock)	−0.049***	−0.062***	−0.044***	−0.007	−0.028	0.000	0.027	0.011	0.034	−0.02	−0.022	−0.02	−0.005	−0.019	−0.002
	[0.015]	[0.015]	[0.015]	[0.030]	[0.030]	[0.030]	[0.029]	[0.029]	[0.029]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.015]
Log(Inter-industry R&D capital stock)	0.004***	0.003***	0.000	0.002	0.001	−0.004	0.006***	0.006***	0.001	0.001	0.001	−0.002	0.002	0.002	0.000
	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Firm size	0.180***	0.172***	0.170***	0.151***	0.140***	0.132***	0.153***	0.142***	0.140***	0.139***	0.139***	0.140***	0.119***	0.113***	0.112***
	[0.014]	[0.014]	[0.014]	[0.026]	[0.026]	[0.026]	[0.024]	[0.024]	[0.024]	[0.018]	[0.018]	[0.018]	[0.021]	[0.021]	[0.021]
Firm age	−0.270***	−0.271***	−0.271***	−0.311***	−0.323***	−0.323***	−0.314***	−0.315***	−0.322***	−0.312***	−0.313***	−0.309***	−0.202***	−0.202***	−0.198***
	[0.039]	[0.039]	[0.039]	[0.061]	[0.061]	[0.061]	[0.053]	[0.053]	[0.053]	[0.057]	[0.056]	[0.056]	[0.063]	[0.062]	[0.063]
Bank loan (BL)	−0.437***	−0.326***	−0.326***	−0.420***	−0.300***	−0.320***	−0.338***	−0.243***	−0.251***	−0.314***	−0.283***	−0.336***	−0.301***	−0.281***	−0.242***
	[0.037]	[0.024]	[0.045]	[0.044]	[0.030]	[0.068]	[0.037]	[0.027]	[0.052]	[0.054]	[0.032]	[0.051]	[0.040]	[0.031]	[0.037]
Imported raw materials consumed (Imp)	−0.006	−0.002	−0.002	−0.011	0.004	0.001	0.004	0.012	0.01	−0.066**	−0.065**	−0.064**	0.001	−0.002	0.004
	[0.018]	[0.018]	[0.018]	[0.029]	[0.028]	[0.029]	[0.024]	[0.023]	[0.023]	[0.026]	[0.026]	[0.026]	[0.024]	[0.024]	[0.024]
BLxR&D capital stock	0.057***			0.061***			0.049***			0.013			0.029***		
	[0.009]			[0.008]			[0.007]			[0.012]			[0.009]		
BLxR&D capital stock(Intra-industry)		0.036***			0.043***			0.032***			0.007			0.028***	
		[0.006]			[0.007]			[0.006]			[0.008]			[0.008]	
BLxR&D capital stock(Inter-industry)			0.012**			0.016**			0.011*			0.009			0.006
			[0.005]			[0.008]			[0.006]			[0.006]			[0.004]
Constant	1.160***	1.190***	1.142***	1.295***	1.357***	1.338***	1.112***	1.146***	1.117***	1.350***	1.346***	1.335***	1.517***	1.561***	1.496***
	[0.149]	[0.149]	[0.149]	[0.234]	[0.232]	[0.235]	[0.218]	[0.219]	[0.219]	[0.206]	[0.205]	[0.204]	[0.238]	[0.237]	[0.237]
Observations	11,595	11,595	11,595	5465	5465	5465	5624	5624	5624	5643	5643	5643	4847	4847	4847
Adjusted R-squared	0.938	0.938	0.938	0.943	0.943	0.941	0.951	0.951	0.951	0.928	0.928	0.928	0.952	0.952	0.952
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	1572	1572	1572	948	948	948	911	911	911	913	913	913	767	767	767

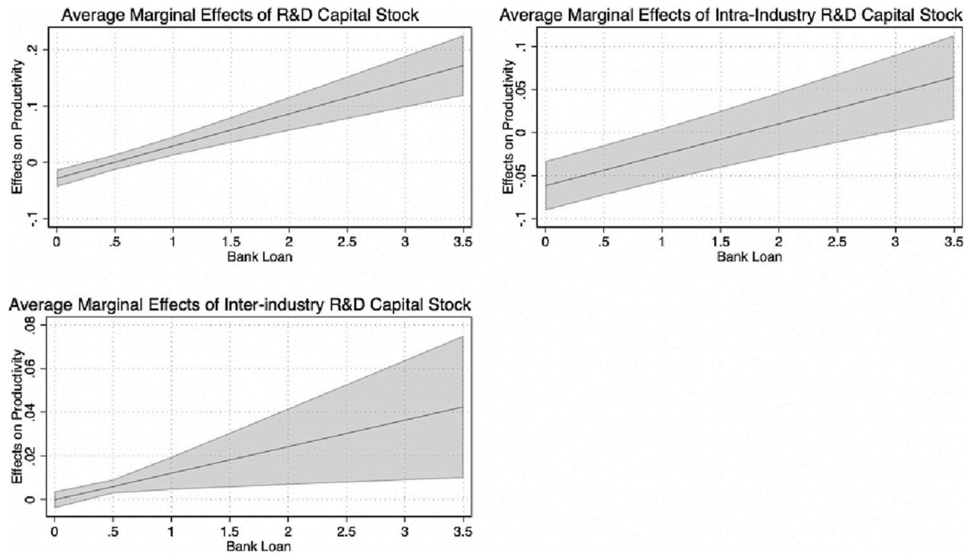

Fig. 2. Average marginal effects of different knowledge spillovers on productivity.
Note: Marginal effects as predicted in Table 5, columns 1–3 (95 % confidence intervals).

spillover pools, all three forms of knowledge stocks appear positive and significant in explaining the productivity of both labour- and capital-intensive R&D-performing panels of Indian firms. Likewise, the disembodied inter-industry knowledge spillovers appear positive and significant for the R&D-intensive and export-intensive firms, contrasting with the total insignificance of all knowledge pools with embodied measures. These differences in results indicate that our use of the industry-level purchases of intermediate goods might be a weak proxy of the knowledge transfer conduit.

Regarding the control variables, we find that firm size is positively and significantly related to productivity. Firm age has a negative and significant impact on productivity, indicating that older firms are less productive. Interestingly, firms' bank loan (access to finance) is negatively and significantly related to productivity, suggesting that a higher level of borrowing (leverage) reduces firms' productivity. Imported raw materials largely appear insignificant in explaining productivity across different categories (panels) of R&D-performing Indian firms. As an exception, the coefficient of *Imp* is negative and significant for the R&D-intensive firms (column 4), indicating that these firms' increased raw material import reduces their productivity.

Table 4 reports the results of the sample of non-R&D-performing firms with embodied spillover pools. For all firms, the coefficient of the intra-industry knowledge spillovers is negative and significant, which is consistent with the intense competition across R&D-performing and non-R&D-performing firms in the same industry. However, inter-industry knowledge spillovers are positive and significant at the 5 % level, indicating that non-R&D-performing firms benefit from the knowledge slipovers emanating from R&D-performing firms of other industries. Results appear qualitatively similar for the export-intensive non-R&D-performing firms (column 4). However, both the labour- and capital-intensive firms that do not perform R&D, benefit from the intra- and inter-industry knowledge spillovers originating from the R&D-performing firms. Overall, the evidence suggests that all four categories (panels) of the R&D-non-performing firms reap productivity benefits from inter-industry knowledge spillovers originating from the R&D-performing firms while there is some evidence of cut-throat competition between the R&D-performing and non-R&D-performing firms within the same industry in India.

5.1. The role of bank financing

We augment our benchmark model using the interactions of firm-level borrowing from banks (BL) with all three measures of knowledge stocks. Table 5 reports the results of the role of access to bank finance on the productivity effect of firm's own R&D capital stock and the inter- and intra-industry knowledge pools. It captures whether firms' access to finance helps or hinders the productivity effects of these knowledge pools.

Taking all firms of the embodied measure, column 1 reports the result of the interaction effect of bank loans and the firm's own capital stock (*BLxR&D capital stock*) on productivity. The interaction effect is positive and significant at the 1 % level. It suggests that firms improve productivity when they invest in R&D and have access to bank loans. In other words, the results suggest that firms with better financial access (or those who are unconstrained in accessing bank credit) and R&D capital stock tend to experience positive and significant productivity effects. To disentangle the interaction effects, we show the average marginal effects of R&D capital stock as well as intra- and inter-industry knowledge spillovers on productivity at different levels of bank loans in Fig. 2. The average marginal effects of R&D capital stock show that if firms undertake their own R&D activities with lower access to bank loans, it reduces productivity. However, firms with higher R&D activities along with greater access to bank loans (with a threshold level of 0.79, which is one standard deviation above the average of BL) tend to achieve higher productivity. In other words, firms' productivity increases with a higher level of R&D capital stock if they have greater access to bank financing. Taking firm categories, we find similar results for the labour-, capital-, and export-intensive firms. Such positive effects on firm-level TFP reflect that credit access matters in productivity via creative innovation.

Taking the full sample, we find that the interaction between bank loans and intra- as well as inter-industry knowledge spillover is also positive and significant. The results of the full sample suggest that Indian firms become more productive when they have greater access to bank loans and higher R&D stock as well as due to within- and between-industry knowledge exchanges. The average marginal effects of intra- and inter-industry knowledge stock in Fig. 2 also show that with a higher level of access to bank borrowing, the productivity of Indian firms increases when there are within or between knowledge exchanges in the industries. The Labour-, Capital-, and Export-intensive firms (except column 15) also show similar results. However, we do not find any significant interaction effect between bank loans and different categories of spillovers for the R&D-intensive firms. When we take the disembodied sample (see Table A3), we find almost similar results except

Table 6
The effect of R&D capital stock on total factor productivity: the role of corporate governance indicators.
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Embodied sample of the R&D-performing firms. Columns 1–3 take all firms in the sample: column 1 reports the results of the interaction term *Eigen × R&D capital stock;* columns 2 and 3 report the results of the interaction terms *Eigen × R&D capital stock (Inter-industry)* and *Eigen × R&D capital stock (Intra-industry)*, respectively. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 4–6, 7–9, 10–12, and 13–15, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms			Labour			Capital			R&D			Export		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Log(R&D capital stock)	0.01	0.014*	0.013*	0.044***	0.049***	0.048***	0.037***	0.040***	0.040***	0.012	0.014	0.014	0.000	0.001	0.000
	[0.008]	[0.008]	[0.008]	[0.014]	[0.014]	[0.014]	[0.011]	[0.011]	[0.011]	[0.012]	[0.012]	[0.012]	[0.010]	[0.010]	[0.010]
Log(Intra-industry R&D capital stock)	−0.053***	−0.054***	−0.053***	−0.001	0.001	−0.001	0.025	0.028	0.026	−0.022	−0.025	−0.023	0.011	0.009	0.011
	[0.017]	[0.016]	[0.017]	[0.036]	[0.035]	[0.036]	[0.034]	[0.033]	[0.034]	[0.017]	[0.017]	[0.017]	[0.017]	[0.018]	[0.017]
Log(Inter-industry R&D capital stock)	0.004***	0.004***	0.002	0.004*	0.004*	0.003	0.006***	0.006***	0.004*	0.001	0.001	0.000	0.003*	0.003*	0.002
	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Firm size	0.179***	0.178***	0.178***	0.134***	0.133***	0.134***	0.136***	0.135***	0.136***	0.158***	0.158***	0.157***	0.113***	0.114***	0.113***
	[0.016]	[0.016]	[0.016]	[0.031]	[0.031]	[0.031]	[0.028]	[0.027]	[0.028]	[0.020]	[0.020]	[0.020]	[0.024]	[0.024]	[0.024]
Firm age	−0.246***	−0.249***	−0.247***	−0.313***	−0.317***	−0.313***	−0.320***	−0.321***	−0.318***	−0.273***	−0.274***	−0.276***	−0.223***	−0.222***	−0.219***
	[0.046]	[0.046]	[0.046]	[0.073]	[0.074]	[0.073]	[0.063]	[0.063]	[0.062]	[0.067]	[0.067]	[0.067]	[0.070]	[0.070]	[0.070]
Bank loan (BL)	−0.242***	−0.243***	−0.242***	−0.203***	−0.203***	−0.203***	−0.167***	−0.167***	−0.168***	−0.278***	−0.279***	−0.279***	−0.196***	−0.196***	−0.196***
	[0.017]	[0.017]	[0.017]	[0.023]	[0.023]	[0.023]	[0.019]	[0.019]	[0.019]	[0.025]	[0.025]	[0.025]	[0.021]	[0.022]	[0.021]
Imported raw materials consumed (Imp)	−0.002	−0.002	−0.003	0.011	0.011	0.01	0.027	0.026	0.026	−0.064**	−0.064**	−0.063**	−0.022	−0.022	−0.023
	[0.021]	[0.021]	[0.021]	[0.035]	[0.035]	[0.034]	[0.026]	[0.026]	[0.026]	[0.032]	[0.032]	[0.032]	[0.027]	[0.027]	[0.027]
Log(Board size)	−0.025*	−0.027*	−0.028**	0.013	0.005	0.009	−0.015	−0.022	−0.018	−0.059***	−0.057***	−0.059***	−0.003	−0.001	−0.004
	[0.014]	[0.014]	[0.014]	[0.020]	[0.020]	[0.019]	[0.020]	[0.020]	[0.020]	[0.021]	[0.021]	[0.021]	[0.023]	[0.023]	[0.023]
CEO duality	0.002	0.002	0.003	−0.014	−0.014	−0.013	−0.007	−0.006	−0.006	0.002	0.002	0.002	0.004	0.004	0.005
	[0.014]	[0.014]	[0.014]	[0.019]	[0.018]	[0.019]	[0.019]	[0.019]	[0.019]	[0.016]	[0.016]	[0.016]	[0.018]	[0.018]	[0.018]
Share of women on board	0.022	0.019	0.022	−0.151	−0.158	−0.154	0.216*	0.212*	0.214*	−0.228	−0.229	−0.227	0.096	0.095	0.096
	[0.089]	[0.089]	[0.089]	[0.114]	[0.114]	[0.114]	[0.111]	[0.111]	[0.111]	[0.148]	[0.148]	[0.149]	[0.117]	[0.117]	[0.117]
Eigenvector centrality (Eigen)	−0.862***	−0.392	−0.952**	−0.923***	0.26	−0.787	−0.504*	0.352	−0.844*	−0.786**	−0.812**	−0.779	−0.337	−0.54	−0.776
	[0.276]	[0.393]	[0.426]	[0.344]	[0.532]	[0.572]	[0.267]	[0.523]	[0.497]	[0.337]	[0.378]	[0.497]	[0.389]	[0.400]	[0.473]
Eigen × R&D capital stock	0.157***			0.155**			0.087			0.177**			0.051		
	[0.057]			[0.065]			[0.054]			[0.076]			[0.090]		
Eigen × R&D capital stock (Intra-industry)		0.045			−0.09			−0.092			0.181**			0.09	
		[0.077]			[0.101]			[0.101]			[0.083]			[0.080]	
Eigen × R&D capital stock (Inter-industry)			0.099*			0.077			0.094			0.092			0.086
			[0.052]			[0.069]			[0.062]			[0.061]			[0.058]
Constant	1.187***	1.182***	1.206***	1.351***	1.345***	1.354***	1.274***	1.269***	1.293***	1.287***	1.237***	1.314***	1.587***	1.581***	1.600***
	[0.188]	[0.190]	[0.189]	[0.296]	[0.303]	[0.299]	[0.283]	[0.287]	[0.284]	[0.255]	[0.256]	[0.255]	[0.281]	[0.281]	[0.278]
Observations	9202	9202	9202	4269	4269	4269	4561	4561	4561	4406	4406	4406	3910	3910	3910
Adjusted R-squared	0.942	0.942	0.942	0.944	0.944	0.944	0.955	0.955	0.955	0.931	0.931	0.931	0.955	0.955	0.955
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	1314	1314	1314	797	797	797	768	768	768	743	743	743	642	642	642

Table 7
The effect of R&D capital stock on total factor productivity.
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run system GMM estimator using the Embodied sample of all R&D-performing firms. We have also followed the same for our categorised firm samples of labour-, capital-, R&D-, and export-intensive activities. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively. Robust standard errors are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms	Labour	Capital	R&D	Export
	1	2	3	4	5
Lagged productivity	0.951***	0.872***	0.942***	0.881***	0.960***
	[0.016]	[0.033]	[0.018]	[0.028]	[0.017]
Log(R&D capital stock)	−0.007	0.034**	−0.007	0.001	−0.009
	[0.013]	[0.016]	[0.016]	[0.018]	[0.015]
Log(Intra-industry R&D capital stock)	0.004	−0.012	0.01	0.035**	0.000
	[0.018]	[0.023]	[0.023]	[0.016]	[0.019]
Log(Inter-industry R&D capital stock)	0.004**	−0.006	0.003*	0.005**	0.003*
	[0.002]	[0.005]	[0.002]	[0.002]	[0.002]
Firm size	0.005	0.018	0.015	−0.019	0.01
	[0.014]	[0.018]	[0.018]	[0.017]	[0.015]
Firm age	0.003	0.013	−0.008	0.002	−0.003
	[0.009]	[0.013]	[0.010]	[0.012]	[0.009]
Bank loan (BL)	−0.082***	−0.099***	−0.072***	−0.090**	−0.110***
	[0.015]	[0.018]	[0.016]	[0.042]	[0.019]
Imported raw materials consumed (Imp)	0.108*	0.088	−0.054	0.012	0.131*
	[0.060]	[0.077]	[0.061]	[0.073]	[0.074]
Constant	−0.037	−0.071	−0.041	0.129	−0.052
	[0.072]	[0.113]	[0.092]	[0.084]	[0.072]
Observations	7936	4428	3998	3965	3495
Number of firms	1339	988	850	850	737
Number of instruments	529	549	552	523	500
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Second-order autocorrelation >0.05	Yes	Yes	Yes	Yes	Yes
Hansen p-value >0.05	Yes	Yes	Yes	Yes	Yes

for the interaction term between bank loans and intra-industry knowledge stock.

5.2. Corporate governance indicators and the role of boardroom connectedness

Table 6 reports the results when our baseline model is augmented by firm characteristics, access to finance proxied by firms' bank loans, the board size, the proportion of females on the board, CEO duality and the measure of boardroom network. This is our most general specification. We are interested in the interactions of Eigenvector centrality with all three measures of knowledge pools.

The Eigenvector centrality is negative and significant in most of the columns, suggesting that the well-connected board on its own does not help firm-level productivity in India; instead, it reduces the productivity of Indian firms. The eigenvector centrality captures the notions of power and prestige of a firm's board. The significantly negative coefficient implies that the mere well-connectedness of boards does not seem to improve their firms' productivity in India. However, the interaction term in the full sample, *Eigen × R&D capital stock*, is positive and significant at the 1 % level, suggesting that a combination of a well-connected board and increased R&D capital stock enhances firm-level productivity. Similar results are observed for the Labour- and R&D-intensive firm categories. The coefficients of *Eigen × R&D capital stock (Intra-industry) and Eigen × R&D capital stock (Inter-industry*) are positive, but the latter is significant at the 10 % level for all firms. These results suggest that a well-connected board enhances the productivity effects of (i) firm's own knowledge stocks across full panel (column 1), labour-intensive panel (column 4), and R&D-intensive firms (column 10). Regarding the spillover effects, a well-connected board appears to enhance the productivity effects of inter-industry knowledge pools for the full panel and intra-industry knowledge pools for the R&D-intensive panel. For the remaining cases, the well-connectedness of boards does not appear to contribute to firm-level productivity either directly or via the knowledge pools. Thus, the role of well-connected company (firm) boards in enhancing firm-level productivity is rather mixed vis-à-vis the embodied measures of firms' knowledge pools. However, while taking the disembodied sample, the productivity effects of well-connected boards appear mostly positive and significant across all analytical trajectories – viz., the full panel as well as the labour-, capital-, R&D-, and export-intensive panel of firms (see Table A4). On balance, well-connected company boards tend to augment firm-level productivity via their knowledge pools.

Results concerning the corporate governance indicators show that the board size significantly negatively affects firm productivity in the full panel and in the R&D-intensive panel. When delineated, board size appears insignificant across labour-, capital- and export-intensive panels of firms. This implies that firms with larger corporate boards either experience lower productivity or the board size effect is ineffectual. Unlike Boubaker et al. (2022), who find a significant negative effect of CEO duality on productive efficiency for French non-financial listed firms, it appears that there are no productivity gains/losses when the CEO is also the Chairman of the firms in India. However, corporate diversity – proxied by the proportion of female directors on the board – shows a limited effect: its effects appear significantly positive across capital-intensive firms. The results from disembodied measures of spillover pools (Table A4) are largely corroborative.

5.2.1. Addressing the endogeneity issue

It is reasonable to treat a firm's accumulated knowledge stock over time, two different sources of knowledge spillovers (intra- and inter-industry knowledge pools) and other control variables as weakly exogenous vis-à-vis TFP. However, we employ the System GMM estimator, proposed by Arellano and Bover (1995) and Blundell and Bond (1998), to estimate Eq. (3) while adding a lagged dependent variable. This estimator is well-known in the literature for estimating dynamic panel data models. It addresses the issue of endogeneity, and it is shown to be a consistent and efficient estimator. The consistency of GMM estimators depends on the validity of instruments and the uncorrelated residuals. We perform Hansen's test of instrument validity as well as the second-

Table 8
The effect of R&D capital stock on total factor productivity: the role of access to bank loans.
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run system GMM estimator using the Embodied sample of all R&D-performing firms. Columns 1–3 take all firms in the sample. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 4–6, 7–9, 10–12, and 13–15, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms			Labour			Capital			R&D			Export		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Lagged productivity	0.955***	0.946***	0.936***	0.905***	0.910***	0.904***	0.960***	0.953***	0.971***	0.914***	0.929***	0.935***	0.967***	0.977***	0.976***
	[0.015]	[0.017]	[0.017]	[0.061]	[0.028]	[0.058]	[0.016]	[0.018]	[0.015]	[0.028]	[0.021]	[0.023]	[0.017]	[0.014]	[0.015]
Log(R&D capital stock)	−0.020***	−0.012	−0.004	−0.068	0	−0.06	−0.036**	−0.015	−0.004	0.006	0.007	0.009	−0.028	−0.004	−0.009
	[0.007]	[0.012]	[0.011]	[0.044]	[0.021]	[0.043]	[0.018]	[0.016]	[0.015]	[0.019]	[0.015]	[0.016]	[0.018]	[0.013]	[0.013]
Log(Intra-industry R&D capital stock)	0.015	0.007	0.011	0.034	−0.006	0.038	−0.015	−0.027	−0.017	0.006	−0.002	0.006	0.003	−0.041*	0.019
	[0.014]	[0.015]	[0.014]	[0.061]	[0.031]	[0.060]	[0.024]	[0.024]	[0.023]	[0.018]	[0.017]	[0.014]	[0.017]	[0.022]	[0.016]
Log(Inter-industry R&D capital stock)	0.003	0.001	0.002	0.005	0.004	0.01	0.004*	0.004*	−0.010**	0.003	0.001	−0.006*	−0.001	0.000	−0.014***
	[0.003]	[0.003]	[0.003]	[0.012]	[0.003]	[0.012]	[0.002]	[0.002]	[0.004]	[0.002]	[0.004]	[0.003]	[0.002]	[0.003]	[0.003]
Firm size	−0.002	−0.001	0.001	0.024	0.011	0.025	0.034*	0.034*	0.029	−0.004	−0.001	−0.002	0.013	0.027	−0.014
	[0.011]	[0.011]	[0.011]	[0.056]	[0.023]	[0.055]	[0.019]	[0.018]	[0.018]	[0.016]	[0.015]	[0.013]	[0.017]	[0.018]	[0.014]
Firm age	−0.002	0.005	0.007	−0.042	0.007	−0.055	−0.007	−0.008	−0.004	0.012	0.005	0.006	−0.014	−0.001	0.011
	[0.006]	[0.010]	[0.009]	[0.129]	[0.010]	[0.130]	[0.009]	[0.010]	[0.008]	[0.010]	[0.010]	[0.008]	[0.023]	[0.008]	[0.010]
Bank loan (BL)	−0.178***	−0.137***	−0.187***	−0.174*	−0.146***	−0.167*	−0.201***	−0.145***	−0.254***	−0.230***	−0.161***	−0.299***	−0.180***	−0.229***	−0.271***
	[0.034]	[0.033]	[0.031]	[0.096]	[0.031]	[0.092]	[0.039]	[0.031]	[0.047]	[0.077]	[0.038]	[0.048]	[0.049]	[0.043]	[0.042]
Imported raw materials consumed (Imp)	0.018	0.01	0.043	0.069	0.008	0.075	0.019	0.024	0.014	0.005	−0.017	0.001	0.087	0.082	0.127*
	[0.050]	[0.052]	[0.052]	[0.121]	[0.060]	[0.124]	[0.055]	[0.057]	[0.051]	[0.061]	[0.069]	[0.063]	[0.068]	[0.063]	[0.065]
BLxR&D capital stock	0.040***			0.036*			0.046***			0.076***			0.047***		
	[0.012]			[0.021]			[0.013]			[0.016]			[0.013]		
BLxR&D capital stock(Intra-industry)		0.030**			0.028**			0.029**			0.037*			0.054***	
		[0.013]			[0.011]			[0.012]			[0.022]			[0.014]	
BLxR&D capital stock(Inter-industry)			0.020***			0.017*			0.032***			0.038***			0.036***
			[0.005]			[0.009]			[0.008]			[0.009]			[0.007]
Constant	0.052	0.049	−0.01	0.2	−0.02	0.138	−0.071	−0.098	−0.053	0.024	0.053	0.055	0.061	−0.062	0.124*
	[0.065]	[0.065]	[0.064]	[0.436]	[0.129]	[0.421]	[0.099]	[0.093]	[0.091]	[0.095]	[0.092]	[0.069]	[0.085]	[0.090]	[0.066]
Observations	7936	7936	7936	3682	3682	3682	3998	3998	3998	3965	3965	3965	3495	3495	3495
Number of firms	1339	1339	1339	872	872	872	850	850	850	850	850	850	737	737	737
Number of instruments	554	535	535	170	528	170	537	537	537	472	491	491	461	479	479
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Second-order autocorrelation >0.05	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value >0.05	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9
Does Intellectual Property Rights (IPR) regime matter in the relationship between R&D capital stock and productivity?
The dependent variable is the Total Factor Productivity (TFP) as proposed by Petrin et al. (2004). We re-run Column 1 of Table 3 using OLS regression controlling for year and firm fixed effects while taking the Embodied sample of the R&D-performing firms. We split the full sample based on the major amendments of the Intellectual Property Rights (IPR) in India. The Pre-IPR is the sample period spanning from 1995 to 2004 while Post-IPR is from 2005 to 2015. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	Pre-IPR	Post-IPR
	1	2
Log(R&D capital stock)	0.008 [0.014]	0.018** [0.007]
Log(Intra-industry R&D capital stock)	0.023 [0.021]	−0.061*** [0.020]
Log(Inter-industry R&D capital stock)	0.001 [0.002]	0.003** [0.001]
Firm size	0.124*** [0.031]	0.152*** [0.018]
Firm age	−0.245** [0.098]	−0.190*** [0.056]
Bank loan (BL)	−0.336*** [0.041]	−0.216*** [0.017]
Imported raw materials consumed (Imp)	0.016 [0.030]	−0.014 [0.019]
Constant	1.263*** [0.331]	0.630*** [0.216]
Observations	2879	8520
Number of firms	913	1369
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Adjusted R-squared	0.959	0.954

order serial correlation test to establish the consistency of system GMM in our dataset. We estimate the second step results of the system GMM estimator along with the robust standard error for finite sample, proposed by Windmeijer (2005).

We report the system GMM results of our benchmark model in Table 7. Taking column 1, we find that inter-industry R&D capital stock is positive and significant at the 5 % level in explaining firm productivity, consistent with Table 3. Inter-industry knowledge stock is also positive and significant in all firm clusters except the Labour-intensive firms. However, own R&D capital stock is positive and significant only for Labour-intensive firms. The R&D-intensive firms appear to benefit from both sources of knowledge spillover pools: both intra- and inter-industry spillover parameters appear positive and significant.[6]

We re-estimate Table 5 using the GMM estimator, reported in Table 8. Columns 1–3 present the results of the full sample of the embodied cluster. The interaction effect of bank loans and firm's own capital stock (*BL×R&D capital stock*) is positive and significant, suggesting that higher R&D and access to bank credits improve productivity. We observe similar results in all clusters of firms. The interaction terms, *BL×R&D capital stock (Intra-industry)* and *BL×R&D capital stock (Inter-industry)*, are also positive and significant not only for the full sample, but also for all clusters of firms. The GMM results for the interaction between bank loans and inter-industry knowledge spillover are consistent with the findings of the fixed effects estimator, demonstrating the robustness of our results.[7]

5.3. Does Intellectual Property Rights (IPR) regime matter for productivity?

Since the early 1990s, India underwent a major institutional change due to economic liberalisation. As a result, many key economic policies, including those related to Intellectual Property Rights (IPR), were introduced. On April 15, 1994, India joined the World Trade Organisation (WTO) by signing the Trade-Related Aspects of Intellectual Property Rights (TRIPS). As a developing country, India had a 10-year (1995–2005) of grace period to transition from the old IPR regime to new IPR regime by 2005. As IPR plays an important role in incentivising firms to engage in knowledge creation, innovating new technologies, and thus becoming more productive, we re-run Column 1 of Table 3 for the Pre-IPR (i.e., before 2005) and Post-IPR (i.e., after 2005) regimes. Our findings would likely stand out, being more prominent during the Post-IPR regime compared to the Pre-IPR one. This is because, before the major amendment to the Indian IPR regime in 2005, Indian firms had little incentive to invest in new innovative activities. A lion share of the R&D expenditure was focused on generating new systems to manufacture existing products (Thakur-Wernz and Wernz, 2022).

However, after the enforcement of TRIPS (i.e., from 2005), the Indian Patent Office (IPO) started accepting both process and product patents. Furthermore, the patent's life increased from five to twenty years. Table 9 presents the results. As alluded above, the results of the Post-IPR regime are more robust than the Pre-IPR one. In particular, the coefficient of own R&D capital stock was positive but insignificant in Table 3. However, it turns significant in the Post-IPR sample. On the other hand, the intra- and inter-industry knowledge spillover turn insignificant in the Pre-IPR sample, but they remain significant in the Post-IPR one. The above results are consistent with the literature that R&D spillover is an important driver of labour productivity and that countries with stronger protection of IPR experience significant knowledge spillovers (see Bournakis et al., 2018). These results provide further support to the notion that after the major amendment of IPR, Indian firms started engaging in R&D activities more, which also led to their higher productivity growth.

5.4. Do import intensity and FDI influence R&D spillover-productivity relation?[8]

As a robustness check, we replace imported raw materials consumed (Imp) variable by import intensity to control for the total imported capital goods and raw materials. Following Bhattacharya et al. (2021), import intensity is measured as the ratio of the amount spent on imported capital and raw materials to sales. As observed by Coe and Helpman (1995), imports are conduits of international knowledge spillovers among trade partners. When an emerging market firm adopts technologies by importing intermediate inputs and capital equipment, it should enhance its TFP through interaction with the changes in its R&D capital stock. However, the direct effect of imports could be negative as it diverts resources while acquiring imported inputs that embody foreign knowledge. Besides, with the economic liberalisation since the early 1990s, domestic firms can also form joint ventures with foreign firms. The presence of foreign firms and/or the proportion of foreign investment in domestic firms could influence their productivity. Therefore, we augment our most general specification with a foreign direct investment (FDI) variable. FDI is the proportion of foreign equity in a domestic

[6] Since intra- and inter-industry knowledge stocks are likely to be exogeneous to the non-R&D firms, therefore we report fixed effects results only for them. However, we ran GMM estimation, and the results were qualitatively similar, which are available from the authors upon request.

[7] As the variability in corporate governance data is limited, we avoid using dynamic GMM estimator and rely on fixed effects estimation.

[8] We thank an anonymous referee for guiding us to this additional helpful analysis.

Table 10
Robustness: do import intensity and FDI influence R&D spillover-productivity relation?
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Embodied sample of the R&D-performing firms. Column 1 takes all firms in the sample. We split the sample based on exporting status of the firms and re-run regression separately for exporting and non-exporting firms in Columns 2–9. The imported raw materials consumed (Imp) variable is replaced by Import intensity. Import intensity is measured as the ratio of the amount spent on imported capital and raw materials to sales. An additional variable FDI is included in the regression. FDI is the proportion of foreign equity in a domestic Indian firm. All other variables are analogous as in Table 6. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms	Exporting firms	Non-exporting firms	Exporting firms	Non-exporting firms	Exporting firms	Non-exporting firms	Exporting firms	Non-exporting firms
	1	2	3	4	5	6	7	8	9
Log(R&D capital stock)	0.026***	0.022**	−0.009	0.031***	0.000	0.023**	−0.01	0.022**	−0.01
	[0.009]	[0.009]	[0.043]	[0.011]	[0.052]	[0.009]	[0.042]	[0.009]	[0.043]
Log(Intra-industry R&D capital stock)	−0.073***	−0.071***	−0.174**	−0.069***	−0.171**	−0.069***	−0.179**	−0.070***	−0.174**
	[0.019]	[0.014]	[0.075]	[0.014]	[0.076]	[0.015]	[0.077]	[0.014]	[0.077]
Log(Inter-industry R&D capital stock)	0.004**	0.004**	−0.002	0.004**	−0.002	0.004**	−0.002	0.004**	−0.002
	[0.002]	[0.002]	[0.005]	[0.002]	[0.005]	[0.002]	[0.005]	[0.002]	[0.005]
Firm size	0.189***	0.169***	0.278***	0.168***	0.271***	0.168***	0.273***	0.169***	0.279***
	[0.018]	[0.017]	[0.072]	[0.017]	[0.074]	[0.017]	[0.071]	[0.017]	[0.073]
Firm age	−0.261***	−0.280***	−0.209	−0.283***	−0.203	−0.282***	−0.176	−0.281***	−0.209
	[0.053]	[0.057]	[0.140]	[0.057]	[0.142]	[0.057]	[0.142]	[0.057]	[0.141]
Bank loan (BL)	−0.232***	−0.213***	−0.338***	−0.212***	−0.326***	−0.213***	−0.333***	−0.213***	−0.337***
	[0.019]	[0.020]	[0.048]	[0.020]	[0.052]	[0.020]	[0.051]	[0.020]	[0.050]
Import intensity	−0.468***	−0.434***	−0.709***	−0.014	0.234	−0.528***	−0.778***	−0.308**	−1.068
	[0.085]	[0.089]	[0.201]	[0.538]	[3.452]	[0.141]	[0.226]	[0.135]	[0.730]
Log(Board size)	−0.038**	−0.047***	0.027	−0.049***	0.031	−0.048***	0.026	−0.047***	0.026
	[0.016]	[0.017]	[0.046]	[0.017]	[0.046]	[0.017]	[0.046]	[0.017]	[0.046]
CEO duality	−0.005	−0.003	0.000	−0.003	0.002	−0.003	0.000	−0.003	−0.002
	[0.016]	[0.017]	[0.046]	[0.017]	[0.047]	[0.017]	[0.047]	[0.017]	[0.047]
Share of women on board	0.032	−0.062	−0.016	−0.053	−0.018	−0.06	−0.027	−0.066	−0.02
	[0.100]	[0.110]	[0.240]	[0.111]	[0.239]	[0.111]	[0.240]	[0.110]	[0.237]
Eigenvector centrality (Eigen)	−0.16	−0.132	0.04	−0.132	0.008	−0.131	0.064	−0.134	0.039
	[0.103]	[0.107]	[0.472]	[0.108]	[0.446]	[0.107]	[0.473]	[0.107]	[0.474]
FDI	0.080*	0.093**	0.01	0.405***	0.691	0.255**	0.041	−0.024	0.254
	[0.041]	[0.042]	[0.139]	[0.116]	[2.440]	[0.123]	[0.609]	[0.068]	[0.255]
Import intensity × FDI				−3.368**	18.584	0.13	−0.961	0.076	0.243
				[1.380]	[14.202]	[0.326]	[1.080]	[0.236]	[10.631]
Log(R&D capital stock) × Import intensity				−0.141	−0.295				
				[0.181]	[1.230]				
Log(R&D capital stock) × FDI				−0.095***	−0.329				
				[0.029]	[0.874]				
Log(R&D capital stock) × Import intensity × FDI				1.245***	−6.171				
				[0.472]	[5.037]				
Log(Intra-industry R&D capital stock) × Import intensity						0.032	0.341**		
						[0.047]	[0.158]		
Log(Intra-industry R&D capital stock) × FDI						−0.052*	−0.033		
						[0.029]	[0.302]		
Log(Intra-industry R&D capital stock) × Import intensity × FDI						0.086	0.388		
						[0.124]	[0.509]		
Log(Inter-industry R&D capital stock) × Import intensity								−0.020	0.050
								[0.016]	[0.093]
Log(Inter-industry R&D capital stock) × FDI								0.012	−0.025
								[0.008]	[0.026]
Log(Inter-industry R&D capital stock) × Import intensity × FDI								0.076*	−0.098
								[0.041]	[1.465]
Constant	1.195***	1.429***	0.205	1.422***	0.197	1.438***	0.126	1.436***	0.202
	[0.202]	[0.207]	[0.622]	[0.208]	[0.640]	[0.209]	[0.638]	[0.207]	[0.627]
Observations	7014	6011	864	6011	864	6011	864	6011	864
Adjusted R-squared	0.942	0.946	0.929	0.946	0.928	0.946	0.929	0.946	0.928
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	1212	1048	223	1048	223	1048	223	1048	223

(Indian) firm, extracted from the Prowess database. Controlling for FDI would help us understand whether foreign firms' presence helps or hinders domestic firms' productivity, as the latter can learn from the former. It would also allow us to check the robustness of our results of the domestic knowledge spillovers while controlling for international knowledge spillovers.

Table 10 reports the results when our most general specification is augmented by import intensity and FDI. Taking embodied measures and all firms, Column 1 shows that the coefficient of import intensity is negative and significant at the 1 % level, indicating that higher imports of capital goods and raw materials result in low productivity. The coefficient of FDI is positive and significant at the 10 % level, suggesting that higher foreign equity ownership in domestic firms improves productivity. Their own R&D capital stock is positive and turns significant after controlling for import intensity and FDI in the model. The sign and significance levels of the intra- and inter-industry knowledge spillovers remain unchanged. These findings lend further credence to the robustness of our earlier results.

We split the sample based on exporting status of firms and re-run the regressions separately for exporting and non-exporting firms. Columns 2 and 3 present the results. The findings of the exporting firms in Column 2 are identical to the ones in Column 1. However, FDI is insignificant in Column 3, suggesting that foreign equity ownership in non-exporting firms does not improve their productivity.

To understand whether the impact of R&D knowledge spillovers on productivity depends on import intensity and FDI, we augment our model by including three-way interaction terms, *Log(R&D capital stock)* $\times$ *Import intensity* $\times$ *FDI*, and re-run the regression separately for exporting and non-exporting firms (Results in columns 4 and 5). The coefficient of the interaction between import intensity and FDI is negative and significant for exporting firms, suggesting that Indian exporting firms do not benefit from importing capital goods and raw materials when they have foreign equity ownership. Furthermore, the *Log(R&D capital stock)* $\times$ *FDI* coefficient is also negative in both Columns 4 and 5 but is significant only for the exporting firms. It indicates that higher own R&D capital stock reduces the productivity of exporting firms if they have higher foreign equity ownership. However, we are primarily interested in the interaction term, *Log(R&D capital stock)* $\times$ *Import intensity* $\times$ *FDI*. We find that the three-way interaction term is positive and significant at the 1 % level, suggesting that higher own R&D capital stock enhances the productivity of exporting firms (not the non-exporting firms) if they import more capital goods and raw materials in the presence of high foreign equity ownership.

Likewise, we also interact import intensity and FDI with intra- and inter-industry knowledge spillovers and report the results in columns 6–9. The interaction term, *Log(Intra-industry R&D capital stock)* $\times$ *Import intensity*, is positive and significant at the 1 % level only for the non-exporting firms. It suggests that the non-exporting firms' productivity increases via intra-industry knowledge spillovers if they import more capital goods and raw materials. On the other hand, the coefficient of *Log(Intra-industry R&D capital stock)* $\times$ *FDI* is negative and significant only for exporting firms, indicating that higher FDI reduces the productivity effects of intra-industry knowledge pool across exporting firms. We do not find any significant three-way interaction effect while taking intra-industry knowledge spillovers with import intensity and FDI. The coefficient of *Log(Inter-industry R&D capital stock)* $\times$ *Import intensity* $\times$ *FDI* is positive and significant at the 10 % level for the exporting firms in Column 8. This result suggests that Indian exporting firms become more productive through inter-industry know-how spillovers if firms have higher import intensity and foreign equity ownership. These results indicate that the higher own and inter-industry R&D capital stock enhances the productivity of exporting firms with foreign equity ownership in the capital structure and when they import more capital goods and raw materials from abroad. It appears that import intensity and FDI complement the impact of knowledge spillovers on the productivity of Indian exporting firms.

6. Conclusions

Given the pivotal role of knowledge spillovers and technological amalgamation in innovation amidst the recent slowdown in global productivity since the global financial crisis of 2008–09, this study employs firm-level panel data from India to investigate the impact of R&D stocks and intra- and inter-industry knowledge spillovers in shaping firm-level productivity. This paper's main message is that inter-industry knowledge spillover pools are important in driving firm-level productivity, suggesting that R&D-performing firms between industries share similar technologies adjacent to their respective technological domain. Aside from domestic R&D spillovers, the interaction and presence of foreign firms via trade and FDI linkages also drive firm productivity, especially for exporting firms. Further, we have shown that spillover effects are significant for specific groups of firms, namely financially unconstrained firms or with greater levels of corporate board connectedness. These results are more prominent when we consider the Post-IPR regime since 2005 relative to the Pre-IPR one.

The findings of this paper are novel relative to the literature as most of the previous studies tend to focus on the spillover effects only. However, this paper, aside from showing that intra- and inter-industry spillovers are important channels of knowledge spillovers, has shown evidence from an emerging market economy that greater access to bank loans and better corporate governance mechanism help in improving the productivity of different clusters of firms. As financial constraints inhibit technology spillovers from foreign to local firms, an important implication of our finding is that policymakers can promote more enabling financial-access policies for firms that are credit constrained and knowledge-intensive. Also, policymakers can promote good corporate governance mechanisms to encourage firms to adopt better-connected boards for knowledge dissemination, and diverse corporate boards to enhance their productivity performance.

CRediT authorship contribution statement

M. Mostak Ahamed: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Kul B. Luintel:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Sushanta K. Mallick:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Summary statistics.
This table reports the Summary statistics of the Dis-embodied sample of all R&D-performing and R&D non-Performing firms separately. *TFP* is the Total Factor Productivity, measured as proposed by Petrin et al. (2004). *Log(R&D capital stock)*, *Log(Intra-industry R&D capital stock)*, and *Log(Inter-industry R&D capital stock)* are R&D knowledge stocks as defined in Table 1. *Firm size* is the Logarithm of total assets while *Firm age* is the Logarithm of the age of firms. *Imp* is the imported raw materials consumed as the share of total raw materials consumption. *Bank loan* is the ratio of total bank borrowing over sales. *Log(Board size)* is the Logarithm of the number of directors in the board in a year. *CEO duality* is a dummy variable that takes 1 if CEO is also the Chairman or else 0. *Share of women on board* is the share of women directors on board in a year. *Eigenvector centrality* represents that a board is well-connected if its direct contacts are also well-connected. It is measured based on the direct links of its well-connectedness.

	Mean	Median	Std. deviation	Min	Max	N
Panel A: R&D-performing firms						
TFP	1.286	1.089	1.154	−1.772	5.349	12,629
Log(R&D capital stock)	3.527	3.122	0.941	2.925	9.687	12,629
Log(Intra-industry R&D capital stock)	8.840	8.996	1.037	2.925	10.961	12,629
Log(Inter-industry R&D capital stock)	11.863	11.976	0.493	7.104	12.342	12,629
Firm size	7.565	7.506	1.652	2.394	11.115	12,629
Firm age	3.442	3.434	0.600	1.099	5.011	12,629
Bank loan	0.317	0.179	0.467	0.000	3.254	12,629
Imported raw materials consumed (Imp)	2.186	2.197	0.401	0.000	3.555	10,025
Log(Board size)	0.036	0.000	0.187	0.000	1.000	10,025
CEO duality	0.030	0.000	0.068	0.000	1.000	10,025
Share of women on board	0.017	0.004	0.046	0.000	1.000	10,025
Eigenvector centrality	0.064	0.037	0.081	0	1	10,025
Panel B: Non-R&D-performing firms						
TFP	1.352	1.180	1.247	−1.772	5.349	40,144
Log(R&D capital stock)						
Log(Intra-industry R&D capital stock)	8.532	8.817	1.065	2.925	10.961	40,144
Log(Inter-industry R&D capital stock)	11.904	12.014	0.447	7.103	12.342	40,144
Firm size	6.029	5.901	1.666	2.394	11.115	40,144
Firm age	3.023	2.996	0.624	0.000	5.017	40,144
Bank loan	0.601	0.203	1.755	0.000	15.235	40,144
Imported raw materials consumed (Imp)	0.166	0.000	0.283	0.000	1.215	40,144
Log(Board size)	1.859	1.946	0.465	0.000	3.664	25,571
CEO duality	0.041	0.000	0.198	0.000	1.000	25,571
Share of women on board	0.039	0.000	0.091	0.000	1.000	25,571
Eigenvector centrality	0.006	0.001	0.019	0.000	0.563	25,571

Table A2
The effect of R&D capital stock on total factor productivity.
The dependent variable is the Total Factor Productivity (TFP) as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Dis-embodied sample of the R&D-performing firms. Column 1 takes all firms in the sample. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 2, 3, 4, and 5, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms	Labour	Capital	R&D	Export
	1	2	3	4	5
Log(R&D capital stock)	−0.003	0.037***	0.033***	0.004	0.001
	[0.007]	[0.011]	[0.010]	[0.011]	[0.010]
Log(Intra-industry R&D capital stock)	0.057***	0.122***	0.108***	0.004	0.013
	[0.017]	[0.029]	[0.023]	[0.027]	[0.024]
Log(Inter-industry R&D capital stock)	0.749***	1.701***	1.236***	0.590**	0.704***
	[0.218]	[0.358]	[0.375]	[0.278]	[0.268]
Firm size	0.148***	0.135***	0.170***	0.137***	0.116***
	[0.010]	[0.015]	[0.014]	[0.015]	[0.016]
Firm age	−0.278***	−0.292***	−0.277***	−0.300***	−0.199***
	[0.038]	[0.061]	[0.051]	[0.056]	[0.057]
Bank loan (BL)	−0.216***	−0.194***	−0.171***	−0.265***	−0.196***
	[0.014]	[0.019]	[0.015]	[0.020]	[0.017]
Imported raw materials consumed (Imp)	−0.008	0.000	0.015	−0.059**	0.001
	[0.017]	[0.029]	[0.022]	[0.025]	[0.023]
Constant	−8.634***	−21.001***	−15.502***	−6.226*	−7.728**
	[2.815]	[4.635]	[4.801]	[3.628]	[3.463]
Observations	12,284	5766	5945	5976	5134
Adjusted R-squared	0.964	0.967	0.969	0.957	0.972
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	1670	1001	961	976	819

Table A3
The effect of R&D capital stock on total factor productivity: the role of access to bank loans.
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Dis-embodied sample of the R&D-performing firms. Columns 1–3 take all firms in the sample. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 4–6, 7–9, 10–12, and 13–15, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms			Labour			Capital			R&D			Export		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Log(R&D capital stock)	−0.033***	−0.003	−0.004	−0.003	0.037***	0.036***	−0.005	0.033***	0.032***	−0.002	0.004	0.005	−0.019*	0.001	0.000
	[0.008]	[0.007]	[0.007]	[0.012]	[0.011]	[0.011]	[0.010]	[0.010]	[0.009]	[0.012]	[0.011]	[0.011]	[0.011]	[0.010]	[0.010]
Log(Intra-industry R&D capital stock)	0.050***	0.050***	0.061***	0.109***	0.121***	0.123***	0.098***	0.106***	0.111***	0.004	−0.001	0.01	0.008	0.005	0.021
	[0.017]	[0.017]	[0.017]	[0.028]	[0.028]	[0.029]	[0.023]	[0.023]	[0.024]	[0.027]	[0.027]	[0.027]	[0.024]	[0.025]	[0.024]
Log(Inter-industry R&D capital stock)	0.729***	0.754***	0.718***	1.593***	1.700***	1.650***	1.179***	1.236***	1.203***	0.615**	0.600**	0.578**	0.691***	0.712***	0.620**
	[0.218]	[0.217]	[0.219]	[0.357]	[0.356]	[0.364]	[0.374]	[0.374]	[0.377]	[0.280]	[0.280]	[0.279]	[0.267]	[0.269]	[0.265]
Firm size	0.154***	0.147***	0.155***	0.148***	0.135***	0.143***	0.178***	0.169***	0.176***	0.136***	0.137***	0.142***	0.121***	0.115***	0.124***
	[0.010]	[0.010]	[0.010]	[0.015]	[0.015]	[0.015]	[0.014]	[0.014]	[0.014]	[0.015]	[0.015]	[0.015]	[0.016]	[0.016]	[0.016]
Firm age	−0.280***	−0.279***	−0.286***	−0.287***	−0.293***	−0.296***	−0.274***	−0.277***	−0.283***	−0.305***	−0.303***	−0.316***	−0.204***	−0.201***	−0.215***
	[0.038]	[0.038]	[0.038]	[0.061]	[0.061]	[0.061]	[0.051]	[0.051]	[0.052]	[0.056]	[0.056]	[0.056]	[0.057]	[0.058]	[0.058]
Bank loan (BL)	−0.416***	−0.349***	−1.732***	−0.418***	−0.21	−1.333***	−0.356***	−0.197	−1.491***	−0.327***	−0.377***	−1.715***	−0.316***	−0.341**	−2.497***
	[0.037]	[0.105]	[0.444]	[0.042]	[0.136]	[0.515]	[0.035]	[0.128]	[0.475]	[0.057]	[0.116]	[0.550]	[0.040]	[0.154]	[0.394]
Imported raw materials consumed (Imp)	−0.011	−0.007	−0.007	−0.008	0.000	0.002	0.012	0.016	0.018	−0.059**	−0.058**	−0.058**	−0.002	0.001	0.009
	[0.017]	[0.017]	[0.017]	[0.028]	[0.029]	[0.029]	[0.022]	[0.022]	[0.022]	[0.025]	[0.025]	[0.025]	[0.023]	[0.023]	[0.023]
BLxR&D capital stock	0.054***			0.059***			0.050***			0.016			0.031***		
	[0.008]			[0.008]			[0.007]			[0.013]			[0.010]		
BLxR&D capital stock(Intra-industry)		0.015			0.002			0.003			0.012			0.016	
		[0.012]			[0.015]			[0.014]			[0.012]			[0.016]	
BLxR&D capital stock(Inter-industry)			0.126***			0.095**			0.110***			0.120***			0.190***
			[0.037]			[0.043]			[0.039]			[0.046]			[0.033]
Constant	−8.261***	−8.622***	−8.322***	−19.518***	−20.981***	−20.432***	−14.649***	−15.482***	−15.162***	−6.499*	−6.289*	−6.123*	−7.465**	−7.727**	−6.788**
	[2.807]	[2.799]	[2.830]	[4.618]	[4.599]	[4.709]	[4.788]	[4.779]	[4.830]	[3.644]	[3.636]	[3.645]	[3.456]	[3.468]	[3.427]
Observations	12,284	12,284	12,284	5766	5766	5766	5945	5945	5945	5976	5976	5976	5134	5134	5134
Adjusted R-squared	0.964	0.964	0.964	0.968	0.967	0.967	0.97	0.969	0.969	0.957	0.957	0.957	0.972	0.972	0.972
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	1670	1670	1670	1001	1001	1001	961	961	961	976	976	976	819	819	819

Table A4
The effect of R&D capital stock on total factor productivity: the role of corporate governance indicators.
The dependent variable is the Total Factor Productivity as proposed by Petrin et al. (2004). We run OLS regression controlling for year and firm fixed effects taking the Dis-embodied sample of the R&D-performing firms. Columns 1–3 take all firms in the sample: column 1 reports the results of the interaction term *Eigen × R&D capital stock;* columns 2 and 3 report the results of the interaction terms *Eigen × R&D capital stock (Intra-industry)* and *Eigen × R&D capital stock (Inter-industry)*, respectively. However, we have categorised firms into labour-, capital-, R&D-, and export-intensive activities and reported the results of these sub-samples in columns 4–6, 7–9, 10–12, and 13–15, respectively. *p*-Values are calculated by the heteroskedasticity-robust standard errors and are presented in brackets. Control variables include firm size, firm age, bank loan, and imported raw materials consumed. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels respectively.

Variables	All firms			Labour			Capital			R&D			Export		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Log(R&D capital stock)	0.004	0.007	0.005	0.046***	0.050***	0.047***	0.038***	0.041***	0.037***	0.006	0.008	0.008	0.005	0.005	0.004
	[0.008]	[0.008]	[0.008]	[0.013]	[0.013]	[0.013]	[0.011]	[0.011]	[0.011]	[0.012]	[0.012]	[0.012]	[0.011]	[0.011]	[0.011]
Log(Intra-industry R&D capital stock)	0.040*	0.034	0.040*	0.096***	0.090**	0.097***	0.104***	0.099***	0.102***	0.004	0	0.002	0.008	0.006	0.009
	[0.021]	[0.021]	[0.021]	[0.035]	[0.035]	[0.035]	[0.029]	[0.029]	[0.029]	[0.035]	[0.035]	[0.035]	[0.025]	[0.025]	[0.025]
Log(Inter-industry R&D capital stock)	0.588**	0.591**	0.576**	1.457***	1.473***	1.464***	1.412***	1.397***	1.347***	0.517	0.534	0.514	0.729**	0.743***	0.711**
	[0.265]	[0.266]	[0.265]	[0.459]	[0.458]	[0.457]	[0.473]	[0.473]	[0.474]	[0.349]	[0.350]	[0.350]	[0.287]	[0.288]	[0.288]
Firm size	0.147***	0.147***	0.147***	0.134***	0.134***	0.135***	0.155***	0.155***	0.156***	0.157***	0.157***	0.156***	0.131***	0.132***	0.132***
	[0.012]	[0.012]	[0.012]	[0.018]	[0.018]	[0.018]	[0.017]	[0.017]	[0.017]	[0.018]	[0.018]	[0.018]	[0.019]	[0.019]	[0.019]
Firm age	−0.267***	−0.269***	−0.262***	−0.313***	−0.320***	−0.309***	−0.292***	−0.293***	−0.293***	−0.276***	−0.278***	−0.276***	−0.231***	−0.228***	−0.231***
	[0.045]	[0.045]	[0.045]	[0.072]	[0.072]	[0.070]	[0.058]	[0.058]	[0.057]	[0.067]	[0.067]	[0.067]	[0.065]	[0.064]	[0.063]
Bank loan (BL)	−0.229***	−0.229***	−0.230***	−0.206***	−0.206***	−0.206***	−0.176***	−0.177***	−0.177***	−0.279***	−0.279***	−0.279***	−0.207***	−0.208***	−0.208***
	[0.016]	[0.016]	[0.016]	[0.022]	[0.022]	[0.022]	[0.017]	[0.017]	[0.017]	[0.025]	[0.025]	[0.025]	[0.020]	[0.020]	[0.020]
Imported raw materials consumed (Imp)	−0.009	−0.01	−0.012	0.013	0.013	0.007	0.035	0.034	0.029	−0.061**	−0.061**	−0.061**	−0.027	−0.028	−0.027
	[0.020]	[0.020]	[0.020]	[0.033]	[0.033]	[0.033]	[0.024]	[0.024]	[0.024]	[0.030]	[0.030]	[0.030]	[0.026]	[0.026]	[0.026]
Log(Board size)	−0.027**	−0.031**	−0.033**	0.018	0.013	0.011	−0.003	−0.006	−0.01	−0.060***	−0.062***	−0.062***	−0.016	−0.018	−0.019
	[0.013]	[0.013]	[0.013]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.020]	[0.020]	[0.020]	[0.021]	[0.021]	[0.021]
CEO duality	0.000	0.000	0.000	−0.012	−0.012	−0.011	−0.009	−0.008	−0.007	−0.006	−0.007	−0.006	0.001	0.001	0
	[0.013]	[0.013]	[0.013]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.016]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
Share of women on board	0.044	0.042	0.05	−0.162	−0.166	−0.155	0.198*	0.196*	0.207**	−0.258*	−0.262*	−0.259*	0.01	0.006	0.013
	[0.085]	[0.085]	[0.085]	[0.116]	[0.116]	[0.116]	[0.105]	[0.106]	[0.106]	[0.144]	[0.144]	[0.144]	[0.111]	[0.111]	[0.111]
Eigenvector centrality (Eigen)	−0.859***	−1.552**	−5.099***	−0.943***	−1.492*	−4.431***	−0.482*	−1.077*	−4.899***	−0.753**	−1.399*	−1.726	−0.121	−1.828**	−3.203*
	[0.268]	[0.667]	[1.637]	[0.335]	[0.822]	[1.529]	[0.249]	[0.566]	[1.680]	[0.323]	[0.797]	[2.668]	[0.395]	[0.831]	[1.710]
Eigen × R&D capital stock	0.156***			0.161***			0.085*			0.162**			0.014		
	[0.052]			[0.060]			[0.048]			[0.069]			[0.090]		
Eigen × R&D capital stock(Intra-industry)		0.166**			0.162*			0.119*			0.154*			0.206**	
		[0.076]			[0.094]			[0.066]			[0.090]			[0.094]	
Eigen × R&D capital stock(Inter-industry)			0.431***			0.375***			0.422***			0.144			0.279*
			[0.141]			[0.133]			[0.145]			[0.230]			[0.148]
Constant	−6.506*	−6.484*	−6.387*	−17.748***	−17.869***	−17.875***	−17.457***	−17.226***	−16.641***	−5.458	−5.613	−5.397	−7.940**	−8.107**	−7.720**
	[3.424]	[3.431]	[3.422]	[5.928]	[5.913]	[5.900]	[6.040]	[6.049]	[6.062]	[4.584]	[4.588]	[4.586]	[3.704]	[3.716]	[3.713]
Observations	9712	9712	9712	4477	4477	4477	4803	4803	4803	4651	4651	4651	4141	4141	4141
Adjusted R-squared	0.966	0.966	0.966	0.967	0.967	0.967	0.972	0.972	0.972	0.958	0.958	0.958	0.973	0.973	0.973
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	1393	1393	1393	842	842	842	810	810	810	790	790	790	684	684	684

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