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Productivity Implications of R&D, Innovation, and Capital Accumulation for Incumbents and Entrants: the Case of Estonia

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PRODUCTIVITY IMPLICATIONS OF R&D, INNOVATION, AND CAPITAL ACCUMULATION FOR INCUMBENTS AND ENTRANTS: THE CASE OF ESTONIA[1]

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Abstract: In this paper, using Estonian Community Innovation Survey data, we study the role of R&D, capital accumulation, and innovation output on productivity for entrants and incumbents. We find that the impact of R&D investment on labour productivity is larger for the entrants compared to the incumbents. Entrants are found to be more productive and more heterogeneous in their total factor productivity (TFP) than the incumbents. Moreover, entrants who innovate are on average, in terms of TFP, 25% more productive than the entrants who do not, while the corresponding figure for the incumbents is 7%. In addition, it is mostly the incumbents who benefit from within-industry knowledge that is produced outside their own firm. Finally, for both entrants and incumbents, embodied technological change through capital accumulation is found to be more effective in generating productivity growth than R&D expenditure.

KEYWORDS: R&D, Innovation, Productivity, Entrants, Incumbents, Spillovers.

JEL Classification: O31, O32

1. INTRODUCTION

The importance of innovative activity by firms for securing economic growth and welfare is generally recognised and widely documented in the scientific literature. Furthermore, there is ample evidence linking innovation to firm-level productivity (for recent surveys, see Hall *et al.*, 2010; Hall, 2011; Mohnen and Hall, 2013). Firms investing in innovation do so to increase their efficiency and improve the goods and services they offer. This increases

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their demand as well as reduces their costs of production, which helps to improve their profits relative to their competitors. However, we also know that returns to R&D vary cross time, sectors and countries and that firms do not contribute uniformly to productivity and productivity growth.

In this paper, we study the productivity implications of R&D innovation and capital accumulation for two important groups of firms in the economy: entrants and incumbents. This study is motivated by the large and growing literature on within-industry reallocation that shape industry dynamics with implications for aggregate productivity. The literature emphasizes selection mechanisms, which characterise industries as collections of firms that are heterogeneous in their productivity, and link firm productivity levels to their performance and survival in the industry (Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Asplund and Nocke, 2006). This heterogeneity induces a selection effect, by which reallocation of market shares to more efficient producers, either through market share shifts among incumbents or through entry and exit, drive aggregate productivity movements. Low productivity plants are less likely to survive and thrive than their more efficient counterparts, creating selection-driven aggregate (industry) productivity increases[1]. Decker *et al.* (2014) document considerable heterogeneity in the contributions entering firms make to growth and show that, given initial size, more productive firms grow faster than the less productive ones.

Much of the recent reallocation literature has been been prompted by the decline in productivity growth and job reallocation coupled with rising intra- and inter-industry dispersion in productivity during the last two decades in the major advanced economies. While various explanations for phenomena such as rising labour adjustment costs and friction have been proffered (Decker *et al.*, 2020), building on models of endogenous technological change, models of firm-level innovation (Klette and Kortum, 2004) and incorporating major elements from the reallocation literature, Acemoglu *et al.* (2018) construct a model of firm innovation and growth that enables an examination of the forces that jointly drive

[1] Foster *et al.* (2008), p. 395, point out that "in reality, however, the productivity-survival link is a simplification. Selection is on profitability, not productivity (though the two are likely correlated). Productivity is only one of several possible idiosyncratic factors that determine profits; however, other idiosyncratic factors may affect survival as well."

innovation, productivity growth, and reallocation.

In Acemoglu *et al.* (2018), incumbents and entrants invest in R&D in order to improve over (one of) a continuum of products. However, firms are heterogeneous (high and low types) in their productivity in innovation. Firms that enter the market are disproportionately of high-quality type but may become low-quality firms with a certain transition probability over time. This heterogeneity introduces a selection effect, with concomitant reallocation occurring with the movement of R&D resources (skilled workers) from less efficient innovators (struggling incumbents) towards more efficient innovators (new firms). They find that conventional R&D subsidies to the incumbents may impede growth by slowing down the reallocation process from incumbents to new entrants. To promote growth and welfare, they propose taxes on the continued operation of incumbents combined with a small incumbent R&D subsidy.

Lubczyk and Peters (2020)(LP hereafter) state that little scholarly research has assessed the dynamics studied in Acemoglu *et al.* (2018) with firm level empirical applications. LP compare the role of R&D activity on productivity growth for entrants and incumbents in Germany, and find that entrants experience significantly larger gains from investments in R&D than incumbents and that returns to R&D for entrants are considerably more heterogeneous than that for incumbents.

Aghion and Jaravel (2015), while reviewing Acemoglu *et al.* (2018), point out that their model, in which R&D investments interact with general equilibrium effects, does not incorporate the notion of absorptive capacity and that it would be fruitful for future research to do so. Aghion and Jaravel (2015), referring to Cohen and Levinthal (1989), state that R&D not only creates new knowledge but also facilitates learning and building absorptive capacity. This is particularly relevant for catching-up economies such as the Central and Eastern European (CEE) countries, which lag behind the technological frontier, and where investing in absorptive capacity through R&D and better education can improve the ability to innovate and/or imitate leading edge technologies (Aghion *et al.*, 2011; Radosevic and Yoruk, 2018). Griffith *et al.* (2004) show empirically that (a) R&D affects both the rate of innovation and technology transfers, and therefore failing to take into account R&D-based absorptive capacity results in large underestimates of the social rate of return to R&D, and (b) country-industries lagging behind the productivity frontier catch-up particularly fast if they invest heavily in R&D. These also imply that many of the policy recommendations in Acemoglu *et al.* (2018) for the US and the technologically advanced economies may not be applicable for the CEE countries.

Parisi *et al.* (2006) show that fixed capital spending by Italian medium-low and low-tech firms increases the likelihood of introducing a process innovation. This, as Parisi *et al.* (2006) argues, suggests that physical capital stock, which is the result of accumulated investment implementing different vintages of technologies, embodies technological progress. Moreover, they show that process innovation is magnified by spending on R&D, which suggests that R&D spending facilitates the absorption of innovations embodied in capital goods purchased by the firm. In catching-up CEE economies (e.g. Estonia) – (a) which tend to grow more due to the imitation activities of the firms, (b) where a much higher share of firms are in medium-tech and low-tech sectors, and (c) where firms are more likely to engage in process innovation – one could therefore expect capital stock accumulation to have significant productivity implications.

Now, in our data we find that less than 40% of the firm-years have positive R&D expenses, but about 75% of the firm-years in the sample have innovated to introduce at least one new product in the market or a new process. This suggests that in Estonia more firms innovate through the "doing, using and interacting" (DUI) mode of innovation rather than "scientific and technologically-based innovation" (STI) (see Jensen *et al.*, 2007). Moreover, as argued in Peters *et al.* (2017), while investments in R&D substantially increase the probability of realising product or process innovations, R&D investment is neither necessary nor sufficient for firm innovation[2]. Focusing on R&D alone will therefore give a partial picture of the productivity implications of innovative activities. We therefore, in addition to estimating the differential productivity elasticity of own R&D for the entrants and the incumbents, study the differential productivity implications of technological innovations.

[2]On page 415, Peters *et al.* (2017) write, "A firm with R&D investment might not realize any product or process innovations, whereas another firm may realize one or both innovations, even without R&D investment. The latter can result from luck, the effect of expenditures on R&D in the more distant past even if the firm is not currently investing, ideas that are brought to the firm by hiring experienced workers or other spillover channels, or changes in the production process that result from learning-by-doing without formal R&D investment."

The main objectives, therefore, of our paper are the following: (i) Given that reallocation, particularly due to entry and exit, accounts for a large proportion of productivity growth (Foster *et al.*, 2008; Syverson, 2011) and since this reallocation, both of production and R&D inputs, is to a large extent due to productivity impacts of R&D and innovation undertaken by heterogeneous incumbents and entrants (Acemoglu *et al.*, 2018), in this paper we study the productivity implications of R&D and innovation for incumbents and entrants. (ii) Given that catching-up economies are more likely to grow by engaging in imitation/learning activities, where R&D also facilities building absorptive capacity, embodied technological change through capital accumulation is likely to have a significant productivity impact. We therefore compare the productivity impact of capital accumulation and the same for R&D for both groups of producers, entrants and incumbents. (iii) Our third objective is to compare the productivity growth impacts of R&D and capital stock for Estonia, a catching-up country, to those in LP, who have undertaken a similar analysis for Germany, a more technologically advanced country, and understand the sources of the difference in the impacts. This, we believe, will inform better growth enhancing policies for Estonia and the CEE countries.

In pursuance of the above objectives, we ask the following questions: First, do entrants benefit more from investing in their own R&D activities than incumbent firms? Second, do we observe a differential learning of entrants and incumbents – and innovating and non-innovating firms among them – from knowledge that is produced outside their own firm boundaries? Third, do entrants and incumbents learn differently through observing the productivity of other firms in close proximity. Fourth, are there differential impacts of technological – product and process – innovation on total factor productivity (TFP) for incumbents and entrants? To answer the above questions, we use Estonian Community Innovation Survey (CIS) data and balance sheet information from Estonian Business Registry data.

To summarise our findings: first, we find that for both the entrants and the incumbents, investing in own R&D significantly improves the productivity of labour. Second, entrants gain significantly more from investing in R&D than the incumbents. Third, it is mostly the incumbents who benefit from within industry knowledge generated by other firms in close proximity. Fourth, among incumbents, within industry regional R&D and productivity spillover effects are higher for non-innovating firms than for innovating ones. Fifth, even though incumbents, on average, have higher labour productivity, the total factor productivity (TFP) for entrants is on average higher. Also, entrants are more heterogeneous in their TFP than incumbents. Sixth, the average difference in TFP between innovators and non-innovators is much higher for entrants than for incumbents. Seventh, we find robust evidence that embodied technological change through capital accumulation is more effective in generating productivity growth than R&D expenditure; moreover, the estimated elasticity with respect to capital is higher for Estonian incumbents compared to German incumbents. Eighth, compared to the German firms, Estonian firms have a lower capacity to translate R&D into productivity gains.

The remainder of this paper is structured as follows. Section 2 reviews related literature and in section 3 we describe the data used for our study. In section 4, we explain the empirical strategy employed in the paper. In Section 5, we present and discuss the empirical results, while section 6 draws concluding remarks.

2. LITERATURE REVIEW

In subsection 2.1 we discuss some literature on the relationship between firm age, innovation and productivity, while in subsection 2.2 we review some relevant studies on innovation, reallocation, and productivity growth for the CEE countries.

2.1. *Innovation among Entrants and Incumbents*

Among the large strand of literature on how different firms contribute to productivity and productivity growth, many studies have examined how dynamics between entrants and incumbents impact aggregate productivity development, highlighting both differential and interrelated effects. In this section, we review some literature on the innovative behaviour of the two groups of firms.

Entrants and incumbents have been described as two different groups of firms (Berchicci and Tucci, 2009; Lubczyk and Peters, 2020). Entrants wanting in experience, still needing to learn about the economic environment in which they operate. Incumbents, on the other hand, have accumulated considerable experience in their competitive environment and command well established capabilities. Entrants, however, are seen as being more expeditious than incumbents due to lack of structural inertia to reorganisation, faster decision-making processes, streamlined operations, and targeted innovation. These result in a timely response to changing industry environments, and also make them more efficient innovators compared to incumbents.

However, entrants are often financially constrained, and investing a large part of the limited resource endowment in R&D activities, which are inherently uncertain, and can pose a significant business risk. Lack of experience and limited expertise may create further complications for the innovation process, especially when unforeseen circumstances arise. On the other hand, however, entry is envisaged as the way in which firms explore the value of new ideas in an uncertain context, and that entry, the likelihood of survival, and subsequent conditional growth are determined by barriers to survival (Audretsch, 1995; Huergo and Jaumandreu, 2004). In this framework, entry is innovative and occurs at a higher rate at the start of an industry (Klepper, 1996) when uncertainty is high; the likelihood of survival is lower the higher the risk; and the growth from successful innovation is higher the higher the barriers to survival. Successful innovation, therefore, is likely to result in substantial relative productivity growth for newly established enterprises. Given that most young firms are small, successful innovation can often disproportionately spur growth and contribute to substantial increases in employment, revenue and future profitability (Haltiwanger *et al.*, 2013). Therefore, one would expect the impact of R&D spending on productivity to be volatile to some extent for new entrants.

Incumbents, having survived through time and participated longer in the market, and have many factors working in their favour as far as innovative activity is concerned. First, even though incumbents often lack the organisational agility of smaller and younger competitors, they may compensate for this with resources – such as financial and marketing capabilities – and innovation capacity built over time (Berchicci and Tucci, 2009). Moreover, an incumbent can build on its existing infrastructure even as existing business experience and infrastructure may enable the incumbent to pursue more ambitious R&D projects. Also, the experience of having conducted successful innovation in the past increases the likelihood of future innovation (Peters, 2009; Raymond *et al.*, 2010) and may help such organisations to achieve higher levels of efficiency in carrying out their R&D activities (Lööf and Johansson, 2014).

The nature of innovations, too, is often different for the two groups of producers. Since incumbents would like to safeguard their profits from the established products and production technologies in place, their innovative activity is therefore more often of an rather incremental nature, whereas young firms, in order to create higher quality products and overtake product lines previously operated by incumbents, are more inclined to exploit new ideas and engage in radical innovation (Acemoglu and Cao, 2015). Besides, radical innovation often entails costly organisational restructuring, which may deter incumbents from undertaking radical innovation (Berchicci and Tucci, 2009).

2.2. *Relevant Studies on Innovation and Reallocation in CEE Countries*

While there are many studies on innovation, reallocation, and productivity growth for the US and Western European countries, there are only a few as far as Central and East European (CEE) countries are concerned. Studies on productivity growth due to selection and reallocation for the CEE countries are by Masso *et al.* (2004) and Bartelsman *et al.* (2013). Masso *et al.* (2004) find that newly formed firms had a higher survival rate than incumbents, and that the reallocation of production factors, especially due to the exit of low productivity units, contributed to the productivity growth. Bartelsman *et al.* (2013) find that, although the covariance between firm-size and productivity, a measure of resource misallocation, is low in Eastern Europe, it has been increasing substantially over the last couple of decades.

Masso and Vahter (2008) point out that to sustain initial growth rates during the transition period in CEE countries, which was based on initial capital accumulation and imitation of technologies applied elsewhere, these countries will need to rely increasingly on their own innovation. Due to their attempts to establish knowledge-based economies and to increase business R&D, there is growing interest in studying the relationship between innovation, productivity and growth in the CEE countries. Among the few studies that have studied the productivity response to R&D while comparing Estonia to developed OECD countries is one by Liik *et al.* (2014), who estimate elasticities using industry level data to conclude that R&D investments play a relatively limited role in determining the productivity and efficiency levels of Estonian industries. Lacasa *et al.* (2017), studying the technological capabilities of CEE economies based on patent data, find that the CEE economies reduced their technological activities drastically after 1990, and that the recovery of CEE economies with respect to technological capabilities is unfolding very slowly. They find that CEE countries innovate in less dynamic technological sectors and contribute only to a limited number of fields with growing technological opportunities.

Recent studies, such as Bruno *et al.* (2019), find that while R&D intensity has been effective in closing the distance to the productivity frontier, R&D embedded in purchased equipment and machinery have played an important role in reducing the distance. Filippetti and Peyrache (2015), studying the role of the technology gap in explaining labour productivity differences in 211 European regions over the years 1995–2007, find that labour productivity growth is driven by capital accumulation and technical change, and that in lagging behind regions, productivity growth is mainly driven by capital accumulation.

3. DATA AND VARIABLES: DEFINITIONS AND DESCRIPTION

In order to study the link between innovation and productivity among entrants and incumbents and how they benefit from knowledge spillovers among them, we use seven waves of the Estonian Community Innovation Survey (CIS) (CIS2006, CIS2008, CIS2010, CIS2012, CIS2014, CIS2016, and CIS2018), which is a survey about innovation activities in Estonian enterprises. The survey adheres to the Oslo Manual, which provides guidelines for the definition, classification, and measurement of innovation (OECD, 1992; 1997; 2005). The questionnaire is sent to firms via mail and participation in the survey is voluntary. Due to cost reasons, starting in 1998, the full questionnaire is only sent out every second year to all firms in the full sample.

A combination of a census and a stratified random sampling is used to collect the CIS data. A census of large enterprises, and a stratified random sample for small and medium sized enterprises from the population is used to construct the data set for every survey. The stratum variables are the economic activity classification (NACE) and the size of each enterprise. The target population includes all legally independent firms located in Estonia that have ten or more employees[3]. The sample is updated every two years to account for

[3] In our data, however, there are more than two per cent firm-year observations for which the number of employees was less than ten. This could be due to firms altering their sizes between the time they were

exiting firms, newly founded firms, and firms that developed to satisfy the selection criteria of the sample.

Firm balance sheet information containing profit and loss statements was obtained from the Estonian Business Registry, which is a census data. Wherever possible, the missing information in the Business Registry data was obtained from EKOMAR, which is survey data and has more detailed information from balance sheets. While the Business Registry data has been maintained since 1993, two years after Estonia's independence, the EKOMAR survey was launched in 2003.

In our empirical analysis, entrant status depends on firm age: entrants are defined as firms that are new to the market and have been active for eight or less years, while incumbents are established firms that have been active for more than eight years. There is no theoretical basis for our definition of an entrant; we, as in Praag and Versloot (2007), follow "apparent conventions" for grouping young firms, whose age in the literature has ranged from three to ten years, and old firms in defining entrants and incumbents.

One of the key variables from the CIS surveys used for our analysis is the R&D expenditure of firms. However, as non-innovative firms in the CIS data are not required to report their R&D expenses, we do not observe R&D expenditure for the non-innovative firms, which are firms that have not innovated any product or process or that have no unfinished innovative activities. The CIS questionnaire, however, allows us to distinguish between "potentially" innovative firms and firms that do not intend to engage in R&D among the non-innovative firms (see Savignac, 2008). This distinction is made on the basis of firm responses to the question on factors that might have thwarted their R&D and innovative activities. We classify non-innovative firms who face such factors as potentially innovative, whereas non-innovating firms that do not face any of these factors are classified as firms that do not intend to engage in R&D activities. For these non-innovators that do not wish to engage in R&D activities, it can be safely assumed that they have no R&D expenses.

Since we do not observe the R&D expenditure of potentially innovative firms, we drop such firms from our analysis. However, non-innovative firms that do not wish to engage in R&D activities are retained. This, as discussed in the next section, allows for us to estimate

selected for the survey and the time they responded to the CIS questionnaire based on previous information on size.

the spillover effects of external knowledge stock as well as productivity for firms with no R&D expenditure and to use the information on the product and process innovation of all firms; firms that have and that do not have R&D expenses.

After removing firms for whom the required balance sheet information was missing and dropping potential innovators among the non-innovative firms, the estimation sample comprised of 5,302 (4,573 incumbents and 729 entrants) firm-year observations from 2,154 firms. The minimum number of observations per firm is 1, the maximum, 7, and the average number is about 2.5 years. In other words, we have an unbalanced panel for the purpose of empirical analysis. There are many reasons why this is so: (1) not all firms are included in every CIS wave, (2) there is entry and exit, and (3) balance sheet information can be missing for firms in CIS the surveys. However, in the Estonian CIS, there is still quite a big overlap of the firms between the different waves.

Estonian firms are relatively young, where the average age of incumbents is 17 years, while that of entrants is 6 years. The definitions of the other variables used in our analysis are stated in Table 1 and descriptive statistics of the variables in the estimation sample are presented in Table 10 and Table 11.

We use two different types of labour productivity measures as our main dependent variables and performance outcomes: revenue productivity and value-added productivity. The former is the ratio of sales to the number of employees, and the latter is the ratio of value-added, the difference between sales revenues and the value of intermediate inputs, to the number of employees. Value-added intends to measure the value in revenue that the firm has generated in excess of pre-made inputs which the firm has procured from other sources.

In order to convert the book value of the gross capital stock into its replacement value, we use the perpetual inventory method described in Salinger and Summers (1983) whenever data in the Business Registry and EKOMAR data is continuous between 2003 and 2018. According to this method, the replacement value of the capital stock is equal to the book value of fixed assets for the first year the firm appears in the data. For the subsequent years, first, the useful life of capital goods, L_t, at time t is calculated as:

$$L_t = \frac{GK_{t-1} + I_t}{DEPR_t},$$

where GK_{t-1} is the reported value of gross property, plant, and equipment at time $t-1$, I_t is the investment in the same for the period t, and $DEPR_t$ is the reported depreciation. Then L_t is averaged over time to obtain L, which is then used in the following formula to obtain the replacement value of the capital stock of a firm in industry k:

$$K_t = \left(K_{t-1} \frac{p_t^k}{p_{t-1}^k} + I_t \right)(1 - 2/L),$$

where p_t^k is the deflator for industry, k. The second term represents the amount of capital stock that depreciates each year and is based on the assumption that economic depreciation is a double declining balance. For new firms and for existing firms that appear again after a gap in later time periods in the data, the book value of the capital stock in the first year is taken as the replacement value. However, for existing firms that after a gap reappear in later years, this method will not yield as good an estimate of the replacement value as for the firms for whom a long, continuous time-series is available.

While not all innovative firms have positive R&D expenditure, the percentage of firms, incumbents and entrants, investing in R&D as well as the amount invested in R&D have generally increased over the years. The majority of the firms, about 79%, in the estimation sample are innovative. Among the innovative firms, the percentage of innovators, or firms that innovated a product or process or both, are quite high; that is, there were few innovative firms that did not invent a new product or process and had unfinished innovative activities. Also, about 7% of firms that have positive R&D expenditure did not introduce any new product or process.

From Table 12, as well as from the summary statistics, we can see that though the incumbents have on average significantly higher labour productivity, larger capital stocks, higher investment and more employees, no systemic differences in the innovative behaviour – propensity to invest in R&D, R&D expenditure, or propensity to innovate – were found between the incumbents and entrants.

In our analysis we include a dummy for north Estonia, which takes value 1 if the company is located in Harju county. Harju county is the biggest of all Estonian counties in terms of population and economic activity, and includes the national capital city, Tallinn. The rational for including this dummy is that firms located in Harju county, which qualifies as the economic hub of Estonia, are likely to be better networked with implications for productivity due to agglomeration. We find that a significantly higher proportion of entrants are based in northern Estonia[4] (see Table 12).

The external knowledge capital, E_{jt}, is intended to capture knowledge spillovers among firms. In our empirical analysis, we differentiate between different types of spillovers: First, intra-industry and inter-industry R&D spillovers to measure to what extent entrants and incumbents differ in their capacity to benefit from R&D knowledge that is available to the firm within and outside its own industry. Secondly, instead of measuring knowledge capital using R&D, we measure intra- and inter-industry regional spillovers using productivity directly. Productivity spillovers take place when firms become more productive simply by being located near other firms. These spillovers can take many forms, including shared ideas or technologies, thick local labour markets, or intermediate input linkages (Audretsch, 1998; Javorcik, 2004; Storper and Venables, 2004).

The measure of the intra-industry knowledge capital of firm i in industry k (based on two digit NACE Rev. 2 codes) in period t is the weighted sum of R&D expenditures per employee of other firms in industry k, $\sum_{j \neq i} w_{ij} \frac{R^k_{jt}}{L^k_{jt}}$, where R_{jt} is the R&D expenditure of firm j, L_{jt} is the number of employees employed by the firm, and the weight, w_{ij}, is the inverse of the geographical distance between the capital of the county in which firm i is located and capital of the county in which firm j belonging to the same industry, k, is located; if firm j happens to be in the same county then w_{ij} is taken as 1. Given that firms also learn through observing productivity directly, analogously, a measure of intra-industry productivity in period t is obtained by taking a weighted mean of the labour productivity of all other firms belonging to the same industry and time period.

The measure of the inter-industry knowledge of firm i in industry k (NACE two digit) in period t is the weighted sum of R&D expenditures per employee of firms in other industries, $\sum_{l \neq k} \sum_j w_{ij} \frac{R^l_{jt}}{L^l_{jt}}$, where, again, the weight w_{ij} is the inverse of the geographical distance between the capital of the county in which firm i is located and the capital of the county in which firm j belonging to a different industry, l, is located. A measure of inter-industry

[4] However, we cannot be 100% sure of firm location, as some companies can operate in a location different from where they are registered, and many companies can operate in several locations, e.g. firms in the retail business.

productivity in time period t is obtained similarly by taking a weighted mean of the labour productivity of all firms belonging to other industries and in the same time period.

In Table 12 we can see that entrants on average are based in or close to regions/counties with significantly higher average productivity; the differences hold for both within and across industry comparisons. However, there appears no significant difference between the entrants and the incumbents in choosing locations where more intra-industry external knowledge is available. Here, we would like to note that even at this broader definition of industry (NACE two digit), about 2% of the firm-year observations had zero intra-industry knowledge flows. This is because a relatively smaller number of firms, about 32%, in the estimation sample invested in R&D.

TABLE 1

Variable Definitions

Variable	Unit	Definition
Entrant	1/0	1 for firm-year observations for which the firm is at most 8 years old
Incumbent	1/0	1 for firm-year observations for which the firm is older than 8 years
Revenue Productivity	log	Labor productivity measured as revenue divided by the number of employees in year t
Value-Added Productivity	log	Labour productivity measured as value-added divided by the number of employees in year t.
Capital	log	Stock of fixed tangible assets in year t calculated using the perpetual inventory method.
Employees	log	Number of employees in year t (in headcounts)
Material	log	Expenses for material and other intermediate inputs in year t
R&D Expenditure	log	Research and development expenses in year t
Innovative	1/0	1 if the firm introduced new products or processes to the market and/or have unfinished innovation
Innovator	1/0	1 if the firm introduced new products or processes to the market
Intra-industry R&D	log	Weighted sum of R&D expenditures by other firms in the same two digit NACE code and year
Inter-industry R&D	log	Weighted sum of R&D expenditures by other firms in the same year with a different two digit NACE code
Intra-industry Productivity	log	Weighted mean of labor productivity of other firms in the same two digit NACE code and year
Inter-industry Productivity	log	Weighted mean of labor productivity of other firms in the same year with a different two digit NACE code
Year dummies	1/0	Set of indicator variables for the year of observation
Industry dummies	1/0	Set of indicator variables for belonging to a two digit NACE (Rev. 2) industry
Firm age	integer	Age variable counting years since a firm took up economic activity
North	1/0	1 if the firm is located in Harju County including Tallinn

For firm $j = 1, \ldots, J$ and time $t = 1, \ldots, T$, we observe revenue (Y_{jt}), labour (L_{jt}), capital (K_{jt}), material inputs (M_{jt}), R&D expenses (R_{jt}), which can also be zero, and (E_{jt}), which is some measure of external knowledge capital.

Now, while a measure of R&D capital stock would be preferred as an innovation input, we are unable to estimate the knowledge capital from the past R&D expenditures using the perpetual inventory method. This is because CIS surveys are conducted once every two years and, secondly, we do not have balanced panel data. Instead, following Crépon *et al.* (1998), Mairesse *et al.* (2005) and more recently Raymond *et al.* (2015) and Baumann and Kritikos (2016), we proxy knowledge capital using current R&D expenditure, R_{jt}. This proxy is based on the implicit assumption that firm R&D investments are strongly correlated (and roughly proportional) to their R&D capital stock measure, and that R&D engagement and intensity persists over time.

The Cobb-Douglas production function when $R_{jt} > 0$ is

$$\begin{aligned} Y_{jt} &= C_0 L_{jt}^{\varphi_l} K_{jt}^{\varphi_k} M_{jt}^{\varphi_m} R_{jt}^{\varphi_r} E_{jt}^{\varphi_e} e^{\omega_{jt}+\epsilon_{jt}} \\ &= C_0 L_{jt}^{\varphi_l+\varphi_k+\varphi_m+\varphi_r} \left(\frac{K_{jt}}{L_{jt}}\right)^{\varphi_k} \left(\frac{M_{jt}}{L_{jt}}\right)^{\varphi_m} \left(\frac{R_{jt}}{L_{jt}}\right)^{\varphi_r} E_{jt}^{\varphi_e} e^{\omega_{jt}+\epsilon_{jt}}, \end{aligned} \tag{4.1}$$

where $e^{\omega_{jt}+\epsilon_{jt}}$ is firm j and time t specific unobserved productivity in the model. The part, ω_{jt}, is the total factor productivity, which is observed by the firms but not by the econometricians, and ϵ_{jt} is an ex-post shock. Dividing both sides by L_{jt} in (4.1) and taking the logarithm, we get

$$y_{jt} = \varphi_0 + \varphi_l^{+} l_{jt} + \varphi_k k_{jt} + \varphi_m m_{jt} + \varphi_r r_{jt} + \varphi_e e_{jt} + \omega_{jt} + \epsilon_{jt}, \tag{4.2}$$

where y_{jt} is the natural log of revenue productivity; $\varphi_l^{+} = \varphi_l + \varphi_k + \varphi_m + \varphi_r - 1$; the lower-case symbols, k_{jt}, m_{jt}, r_{jt}, and e_{jt}, on the RHS represent natural logs of $\frac{K_{jt}}{L_{jt}}$, $\frac{M_{jt}}{L_{jt}}$, $\frac{R_{jt}}{L_{jt}}$, and E_{jt} respectively; and $\ln(C_0) = \varphi_0$.

As discussed in the section on data, not all firms, innovating or otherwise, have positive R&D expenditure. We nonetheless keep such firms in our analysis for two reasons. First, this allows us to estimate the spillover effects of external knowledge capital for firms that do not engage in R&D. Second, as discussed below, we are able to use the information on product and/or process innovation, even in firms that do not have positive R&D expenses, to endogenise the evolution of ω_{jt} and assess the implications of innovation on total factor productivity.

The production function when R&D capital, R_{jt}, is equal to zero is given by

$$(4.3) \qquad Y_{jt} = A_0 L_{jt}^{\varphi_l^0+\varphi_k^0+\varphi_m^0} \left(\frac{K_{jt}}{L_{jt}}\right)^{\varphi_k^0} \left(\frac{M_{jt}}{L_{jt}}\right)^{\varphi_m^0} E_{jt}^{\varphi_e^0} e^{\omega_{jt}+\epsilon_{jt}}.$$

Again dividing both sides by L_{jt} in (4.3) and taking the logarithm, we get

$$(4.4) \qquad y_{jt} = a_0 + \varphi_l^{0+} l_{jt} + \varphi_k^0 k_{jt} + \varphi_m^0 m_{jt} + \varphi_e^0 e_{jt} + \omega_{jt} + \epsilon_{jt},$$

where $\varphi_l^{0+} = \varphi_l^0 + \varphi_k^0 + \varphi_m^0 - 1$ and $a_0 = \ln(A_0)$.

As can be seen from eq. (4.2) and eq. (4.4), we allow the coefficients of the input variables for firms that engage in R&D and firms that do not to be different. We can estimate (4.2) and (4.4) by pooling the data and estimating the following equation:

$$\begin{aligned} y_{jt} =& \varphi_0 + D_{jt}^0(a_0 - \varphi_0 + \varphi_l^{0+} l_{jt} + \varphi_k^0 k_{jt} + \varphi_m^0 m_{jt}) \\ (4.5) \qquad & + (1 - D_{jt}^0)(\varphi_l^+ l_{jt} + \varphi_k k_{jt} + \varphi_m m_{jt} + \varphi_r r_{jt}) + \varphi_e e_{jt} + \omega_{jt} + \epsilon_{jt}, \end{aligned}$$

where D_{jt}^0 is a dummy variable that takes the value 1 when R&D expenditure is zero.

An equivalent of (4.5) when y_{jt} is the value-added productivity[5] is given by

$$\begin{aligned} y_{jt} =& \beta_0 + D_{jt}^0(a_0 - \beta_0 + \beta_l^{0+} l_{jt} + \beta_k^0 k_{jt}) \\ (4.6) \qquad & + (1 - D_{jt}^0)(\beta_l^+ l_{jt} + \beta_k k_{jt} + \beta_r r_{jt}) + \beta_e e_{jt} + \omega_{jt} + \epsilon_{jt}, \end{aligned}$$

Here, the intermediate input, m_{jt}, does not enter the log transform of the value-added production function[6]. The term, ω_{jt}, again, is the anticipated productivity shock, which is

[5] With a slight abuse of notation, we denote log transforms of value-added productivity and revenue productivity by y.

[6] The value-added production function in log terms in (4.6) can be derived from the following gross-output Leontief production function, where material input is proportional to output:

$$Y_{jt} = \min\{B_0 L_{jt}^{\beta_l} K_{jt}^{\beta_k} R_{jt}^{\beta_r} E_{jt}^{\beta_e} e^{\omega_{jt}}, \beta_m M_{jt}\} e^{\epsilon_{jt}} \text{when } R_{jt} > 0.$$

This implies that value-added, $Y_{jt} - M_{jt}$, can be written as $Y_{jt} - M_{jt} = (1 - \frac{1}{\beta_m}) B_0 L_{jt}^{\beta_l} K_{jt}^{\beta_k} R_{jt}^{\beta_r} E_{jt}^{\beta_e} e^{\omega_{jt}+\epsilon_{jt}}$ when $R_{jt} > 0$. Similarly, when $R_{jt} = 0$, we have $Y_{jt} - M_{jt} = (1 - \frac{1}{\beta_m^0}) A_0 L_{jt}^{\beta_l^0} K_{jt}^{\beta_k^0} E_{jt}^{\beta_e^0} e^{\omega_{jt}+\epsilon_{jt}}$. Scaling K_{jt} and R_{jt} by L_{jt}, then dividing throughout by L_{jt}, and then taking logarithm of the value-added production functions when $R_{jt} > 0$ and when $R_{jt} = 0$ and combining the two as in (4.5), we get eq. (4.6).

observed by the firms but not by the econometricians and ϵ_{jt} is an ex-post shock.

We estimate equation (4.5) using random effects (RE), fixed effects (FE) and the control function method in Olley and Pakes (1996) (OP), while equation (4.6) is estimated using the control function method in Ackerberg *et al.* (2015)(ACF). The random effects estimator makes a strong assumption that the productivity shocks in equation (4.5) are time invariant ($\omega_{jt} = \omega_j$) and are independent of other covariates in the equation. This implies that input choices are made independently of the firm's fixed productivity level. Under this assumption pooled random-effects is an unbiased estimator. However, a violation of this assumptions leads to inconsistent results. The fixed-effect estimator relaxes the assumption that the time invariant ω_j is independent of the other covariates in the equation.

The unobserved productivity shocks, ω_{jt}, that are known to the firm when it makes its input choices, however, are likely to vary with time and are correlated with ω_{jt}. To resolve the issue of endogeneity, OP(OP) and Levinsohn and Petrin (2003) (LePe) have developed "control function" approaches, which involve the use of economic theory to derive a "proxy" for the anticipated shock productivity, ω_{jt}, by assuming that they can be inverted out from certain firm inputs if the firm has adjusted these optimally in response to the ω_{jt} it observed.

Given certain limitations of the OP's and LePe's method, among them chiefly the problem of "functional dependence," ACF developed yet another control function approach. The problem of functional dependence in ACF refers to the problem of the non-identification of the labour coefficient in (4.5)[7]. ACF's method differs crucially from LePe and OP in the timing of the investment and input decisions and the kind of control function or proxy for the anticipated shock, ω_{jt}. Also, in ACF a value-added production function is estimated.

Below we state the main identifying assumptions in OP and ACF.

ASSUMPTION 1 *(Information Set) The firm's information set at t, $\mathcal{I}_{jt}$, includes current and past productivity shocks $\{\omega_{j\tau}\}_{\tau=0}^{t}$ but does not include future productivity shocks $\{\omega_{j\tau}\}_{\tau=t+1}^{\infty}$. The transitory shocks ϵ_{jt} satisfy* $\mathrm{E}\{\epsilon_{jt}|\mathcal{I}_{jt}\} = 0$.

[7] ACF show that under the data generating process in OP and LePe, labour is a deterministic function of the set of variables that need to be non-parametrically conditioned. Hence, these variables are conditioned, and there is no variation in labour left to identify the labour coefficient.

Assumption 2 *(Productivity Evolution) Productivity shocks or the unobserved heterogeneity evolve according to the first order Markov Process, i.e.,* $p(\omega_{j,t+1}|\mathcal{I}_{jt}) = p(\omega_{j,t+1}|\omega_{jt})$*, where the distribution,* $p(\omega_{j,t+1}|\omega_{jt})$*, which is stochastically increasing in* ω_{jt}*, is known to the firm.*

In the above assumption, the evolution of a firm's productivity is exogenous. Griliches (1979) points out that while R&D affects output, R&D is determined both by past output and the expectations of future output. And thus past R&D efforts and innovation output affect the evolution of productivity, ω_{jt}, and ω_{jt} and expectations of ω_{jt+1} affect the endogenous choice of R_{jt}. We therefore, in a manner similar to Doraszelski and Jaumandreu (2013)(DJ) and Peters *et al.* (2017), endogenise productivity evolution by making ω_{jt} depend on a measure of innovation output; more specifically, productivity, ω_{jt}, is modelled to evolve according to a controlled Markov process, $p(\omega_{jt}|\omega_{j,t-1}, I_{j,t}, I_{j,t-1})$, where $I_{j,t}$ is an indicator variable that takes the value 1 if firm j innovated at least one product or process in period t[8]; here the assumption is that $I_{j,t}$, too, is a result of R&D efforts in the past.

The Markovian assumption implies that

$$\omega_{jt} = \mathrm{E}(\omega_{jt}|\omega_{j,t-1}, I_{j,t}, I_{j,t-1}) + \xi_{jt} = g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1}) + \xi_{jt}. \tag{4.7}$$

In the above, productivity ω_{jt} in period t has been decomposed into expected productivity, $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})$, and a random shock, ξ_{jt}. While the conditional expectation function $g(.)$ depends on the already attained productivity $\omega_{j,t-1}$ and $I_{j,t}, I_{j,t-1}$, ξ_{jt} does not. The residual, ξ_{jt}, by construction is mean independent of $\omega_{j,t-1}$ and $I_{j,t}, I_{j,t-1}$; we, in addition, assume complete independence. As discussed in DJ, the productivity innovation, ξ_{jt}, represents the uncertainties that are naturally linked to productivity and the uncertainties inherent in the innovation process such as degree of applicability and success in implementation. The two step control function procedure proposed in ACF is employed to estimate the conditional expectation function $g(.)$ non-parametrically along with the parameters of the production function[9].

[8] DJ endogenise productivity evolution by including a measure of R&D investment, $p(\omega_{jt}|\omega_{j,t-1}, R_{j,t-1})$, while in Peters *et al.* (2017) productivity evolves as $p(\omega_{jt}|\omega_{j,t-1}, d_{jt}, z_{jt})$, where z_{jt} and d_{jt} are discrete variables equal to 1 if the firm j realises a process or product innovation in year t and 0 otherwise.

[9] We use the STATA's "prodest" command, which has been developed by Rovigatti and Mollisi (2018),

Assumption 3 *(Timing of Input Choices) Firms accumulate capital according to:*

$$k_{jt} = \kappa(k_{j,t-1}, i_{j,t-1}),$$

where investment $i_{j,t-1}$ is chosen in period $t-1$. In OP, labour input l_{jt} is non-dynamic and chosen at t, whereas in ACF, labour input l_{jt} has potential dynamic implications and is chosen at period t, period $t-1$, or period $t-b$ (with $0 < b < 1$).

Assumption 4 *(Scalar Unobservable) In OP, firm investment decisions are given by:*

$$i_{jt} = f_t(k_{jt}, r_{jt}, x_{jt}, \omega_{jt}). \tag{4.8}$$

where i_{jt} is the log of investment by firm j in time t and x_{jt} is the set of other state variables, which, for example, include measures of external knowledge. In ACF, firm intermediate input demand is given by:

$$m_{jt} = f_t(l_{jt}, k_{jt}, r_{jt}, x_{jt}, \omega_{jt}). \tag{4.9}$$

Assumption 5 *(strict monotonicity) In OP investment in (4.8) is strictly increasing in ω_{jt}, and in ACF, intermediate inputs in (4.9) is strictly increasing in ω_{jt}.*

Given the above assumptions, a proxy for ω_{jt} in OP is obtained by inverting the investment demand in (4.8), $\omega_{jt} = f_t^{-1}(k_{jt}, r_{jt}, x_{jt}, i_{jt})$, while in ACF, the proxy is obtained by inverting the intermediate input demand in (4.9), $\omega_{jt} = f_t^{-1}(l_{jt}, k_{jt}, r_{jt}, x_{jt}, m_{jt})$.

5. RESULTS

In the following, we compare the impact of investing in internal innovation on productivity among entrants and incumbents and also how they benefit from knowledge spillovers. First, in subsection 5.1, we estimate the production function in equations (4.5) and (4.6), focusing on the average rate of return to internal R&D investments for the group of entrants and incumbents. We next augment the production function by adding external knowledge

to implement the control function methods in OP and in ACF. The endogenous() option, when using prodest to implement the method in ACF, allows users to specify one or more variables that endogenously affect the dynamics of productivity, $\omega_{j,t}$.

capital in subsection 5.2. This allows us to study the differential learning of entrants and incumbents from knowledge that is produced outside its own firm boundaries. In subsection 5.3, we estimate the impact of product and process innovation on total factor productivity for the two group of producers, incumbents and entrants. Finally, in subsection 5.4, we compare our estimated elasticities of productivity with respect to internal R&D and capital stock with those estimated in LP, who have undertaken a similar analysis for Germany.

5.1. *Average Returns to Own R&D and Capital Accumulation for Entrants and Incumbents*

Using the empirical framework outlined in section 4, we first study how the productivity effects of (1) innovation effort as proxied by R&D expenditure and (2) capital accumulation differ between entrants and incumbent firms. Table 2 reports the results of RE and FE regressions of the production function in (4.5). As can be seen from the table, the FE estimates, especially for entrants, have large standard errors. This is most likely because there is little within-firm variation in our panel data: 35% of the incumbents are observed just once and 22% are observed twice, while the corresponding figures for the entrants are 56% and 24%. Given that the fixed-effects model only makes use of within-panel variation, it is quite likely that FE estimates turn out to be poor, and accordingly we rely less on the FE estimates in our interpretation.

In Table 2, we also display the results of estimating equation (4.5) using the methodology in OP and equation (4.6) using the method in ACF. The dependent variable when employing the methodology in OP is revenue productivity. Since identification in the ACF model is limited to value-added production functions, we use value-added productivity as the dependent variable. Since in OP a proxy for ω_{jt} is obtained by inverting the investment demand in (4.8) and because for many firm-year observations investments in fixed assets were zero, the number of observations when employing the OP methodology is lower.

Due to the log-linear specification, the resulting coefficients of the input variables can be interpreted as elasticities. We find that the productivity elasticity of R&D expenditures is significantly positive for both entrants and incumbents. However, on average, entrants benefit more from investing an additional 1% in R&D than incumbents: the difference in the magnitude of the output elasticity of R&D expenditures for entrants and incumbents is relatively the same across all methods: FE, RE, OP, and ACF. These results are consistent with the theoretical argument that young firms that do not have a well established product portfolio on the market benefit more from investing in R&D because R&D enables them to develop new products and catch up with incumbents. Furthermore, during this period, they are more inclined to exploit new ideas and invest in radical innovation which in turn may lead to higher productivity gains.

We also find that both incumbents and entrants seem to experience larger productivity gains from additional capital inflow than R&D expenditure. Also, among the incumbents the average elasticity of non-R&D performing firms was found to be marginally higher than those with positive R&D, though the difference was found to be significant only while employing the ACF method. These results suggest that, as far as Estonia is concerned, on average "embodied technological change" through capital accumulation has been more effective in generating productivity growth (Castellani *et al.*, 2019).

The results in Table 2 suggest that both entrants and incumbents experience productivity gains from material inflow. We find that the estimates of $\varphi_l^+ = \varphi_l + \varphi_k + \varphi_m + \varphi_r - 1$ and $\varphi_l^{0+} = \varphi_l^0 + \varphi_k^0 + \varphi_m^0 - 1$, which are the coefficients of $\log(\text{Employees}) \times (1 - D^0)$ and $\log(\text{Employees}) \times D^0$ respectively in the revenue production function (4.5), are significantly negative for the incumbents. The negative estimates of φ_l^+ and φ_l^{0+}, however, do not imply that productivity is decreasing for incumbents with additional employment; it only suggests that the cumulative share of some of the inputs is less than 1. In a separate set of regressions, which we do not report here due to lack of space, we estimated the revenue production function when output and inputs were not scaled by number of employees. In these regressions we found the share of employment, φ_l and φ_l^0, to be quite high.

As far as age is concerned, it can be revealed from the OP estimates that there is some evidence that among all entrants, the older ones are more productive. This suggests learning effects for the entrants in terms of productivity improvements with every additional year the firm survives on the market. However, the negative and significant coefficient of firm age for incumbents indicates that these learning effects associated with firm age become much smaller and phase out in later stages of firm life.

The RE estimates and the control function estimates suggest that firms located in north-

TABLE 2

Productivity Effects of R&D and Capital Accumulation for Entrants and Incumbents

	Incumbent				Entrant			
	FE	RE	ACF	OP	FE	RE	ACF	OP
log(Employees)$\times(1-D^0)$	-0.231***	-0.039***	0.074***	-0.052**	-0.035	0.044	0.028	0.053**
	(0.020)	(0.015)	(0.001)	(0.022)	(0.081)	(0.043)	(0.025)	(0.022)
log(Employees)$\times D^0$	-0.228***	-0.025***	0.077***	-0.044**	-0.058	0.028	0.020	0.050**
	(0.019)	(0.014)	(0.002)	(0.019)	(0.072)	(0.034)	(0.016)	(0.024)
log(Capital/Employees)$\times(1-D^0)$	0.052***	0.104***	0.185***	0.113***	-0.001	0.083***	0.187***	0.141***
	(0.009)	(0.008)	(0.002)	(0.013)	(0.037)	(0.023)	(0.041)	(0.037)
log(Capital/Employees)$\times D^0$	0.056***	0.115***	0.192***	0.154***	0.038	0.096***	0.168***	0.079***
	(0.008)	(0.007)	(0.000)	(0.009)	(0.030)	(0.018)	(0.031)	(0.028)
log(Material/Employees) $\times(1-D^0)$	0.101***	0.135***		0.265**	0.085**	0.192***		0.082**
	(0.008)	(0.008)		(0.026)	(0.032)	(0.023)		(0.037)
log(Material/Employees)$\times D^0$	0.118***	0.150***		0.220***	0.072***	0.195***		0.184***
	(0.007)	(0.006)		(0.015)	(0.028)	(0.018)		(0.021)
log(R&D/Employees)	0.005*	0.008**	0.019***	0.014***	0.030**	0.030***	0.053***	0.030*
	(0.003)	(0.003)	(0.005)	(0.003)	(0.012)	(0.011)	(0.019)	(0.017)
D^0: Dummy Zero R&D	-0.015	-0.064	0.018***	-0.011	0.239	0.17	0.085**	0.119***
	(0.056)	(0.058)	(0.000)	(0.016)	(0.235)	(0.187)	(0.017)	(0.016)
Age	-0.048***	-0.009***	-0.004***	0.007	0.015	-0.013	0.032	0.047*
	(0.011)	(0.003)	(0.001)	(0.009)	(0.027)	(0.011)	(0.023)	(0.028)
North Estonia	-0.010	0.272***	0.181***	0.240***	0.092	0.231**	0.200***	0.165***
	(0.068)	(0.030)	(0.001)	(0.004)	(0.194)	(0.064)	(0.026)	(0.012)
Intercept	11.881***	9.070***			9.644***	7.686***		
	(0.278)	(0.171)			(0.550)	(0.774)		
No. of Observations	4573	4573	4573	4147	729	729	729	657

Note: Dependent Variables: log(Value-Added/Employees) when employing ACF and log(Revenue/Employees) when employing FE, RE, and OP. Every specification includes Time and Industry Dummies.

Standard Errors in Parenthesis. Significance levels : $*$: 5% $**$: 1% $***$: 0.1%

ern Estonia, which is the economic hub of the nation, are more productive; this suggests that firms in northern Estonia benefit from a positive agglomeration effect. The control function estimates also suggest that firms, especially entrants, are more productive if they do not invest in R&D. This result, however, is not robust across specifications and methods.

Finally, we would like to point out that the difference between the estimated elasticities with respect to employment, capital and material inputs for the R&D performing and non-R&D performing firms did not turn out to be significant; the only exception being estimated elasticity with respect to capital for incumbents while employing the ACF method. Consequently, in the rest of the paper we estimate common coefficients for the three inputs.

5.2. *Spillover Effects*

As knowledge created in one firm or organisation spreads, in addition to using the internally generated stock created by investing in R&D, firms use external knowledge developed and held by other firms. Knowledge spillovers are thus likely to affect firm-level innovation and labour productivity. Simple examples of such spillovers include firms benefiting from informal knowledge spillovers, especially if they happen to operate in sectors with higher average R&D spending. Firms also learn directly from knowledge spillovers when partnering with customers, suppliers, or entities with whom they share a supply chain, especially if the collaboration is to foster innovation. Besides, firms also learn from competitors who provide a visible performance benchmark in market competition.

These spillover effects are highly relevant for both firms and policy makers, as they point to situations where the benefits of accumulating knowledge in one firm result in performance and productivity gains in a larger agglomeration or group of firms, further resulting in a sub-optimal low level of R&D from a social point of view. Therefore, a key question related to the productivity effects of innovation is the degree to which a firm's innovation impacts other firms' performances.

In this section, we examine the productivity benefits that entrant and incumbent firms gain from geographic proximity to external knowledge capital of either firms inside or outside of their own core industry (intra- versus inter-industrial spillovers). In the following three subsections, we focus on different types of external knowledge capital. While subsection 5.2.1 measures spillovers using the sum of R&D expenditures of other firms, subsection 5.2.2 measures knowledge spillovers using the average productivity of other firms.

5.2.1. *Inter- and Intra-Industrial R&D Spillovers*

External knowledge may serve as an important learning resource as it may complement the internal knowledge at the disposal of the firm, in particular if external knowledge originates from different knowledge sources or is the result of alternative attempts at solving common technical challenges (Audretsch and Belitski, 2020). Research on knowledge spillovers at the micro-level, however, finds that the different mechanisms through which spillovers occur are indeed localised to a large extent (see Audretsch, 1998; Storper and Venables, 2004; Ponds *et al.*, 2010). Besides the importance of local labour markets and spin-off dynamics, studies have emphasized the role of networking between individuals and between organizations as a mechanism for knowledge spillovers that takes place at the regional level. For each firm, then, we define external knowledge capital as the accumulation of knowledge that is generated by other firms that are geographically close to the focal firm.

Since knowledge spillovers can take place both within and between industries, we further differentiate the group of other firms into those firms that are within and those that are outside of the focal firm's own industry, and accordingly construct measures of inter- and intra-industry knowledge capital (see section 4 for the definition of the two). These measures of external knowledge capital are then added to the production functions in equations (4.5) and (4.6). To test if there is differential impact of knowledge spillover for innovating and non-innovating firms, we interact the measures with two binary variables: one that takes the value 1 if the firm is innovating and zero otherwise, and the other that takes the value 1 if the firm is non-innovating and zero otherwise. Table 3 illustrates the estimated results using these measures of external knowledge capital in the productivity functions. For the purpose of exposition, in the table we include the coefficient estimates of only the knowledge related variables: firm's own R&D expense as a measure of internally generated knowledge stock and measures of external knowledge generated within and between industries. For the variables whose coefficient estimates have not been displayed, the coefficient estimates are almost the same as the estimates in Table 2.

Now, what we find in our data is that the average R&D expenditure and average labour productivity of firms is higher in counties/regions where there is a higher concentration (number of firms/geographical area of the county) of firms. Moreover, we find that there is a positive correlation between entrants' R&D expenses (productivity) and the average R&D expenses (productivity) of other firms situated in the same region. It therefore seems that location is not random but a deliberate choice made by the firms. It is therefore conceivable that a positive correlation between firm productivity is partly determined by high productivity entrants establishing themselves geographically close to the already productive incumbents. In other words, measures of external knowledge capital, through endogenous choice of location, and firm total factor productivity, $\omega_{j,t}$, are correlated. The endogeneity of measures of external knowledge capital is accounted for by treating measures of external knowledge capital, be they based on R&D expenses or labour productivity, and a dummy for north Estonia as state variables when using the OP and ACF methods.

The FE, the ACF and OP estimates suggest that only the incumbents benefit from external knowledge within their own industry. The OP estimate seems to suggest that incumbents also benefit from knowledge capital outside their industry. In other words, these results seem to indicate that mature firms are on average better at incorporating diverse knowledge that stems from sources both within and outside their industry. The regression results also show that for the incumbents, the social returns to intra-industry knowledge capital are comparable or even higher than the private returns to R&D.

The OP, ACF, and the FE estimates, too, suggest that non-innovating firms among the incumbents benefit more from external knowledge than innovating firms. Given that there exists complementarity between absorptive capacity and external knowledge and that at sufficiently low levels of absorptive capacity further increases in external knowledge may not increase marginal private incentives to build absorptive capacity to benefit from it (see Aghion and Jaravel, 2015), the results seem to indicate that non-innovating incumbents do invest in building absorptivity capacity to benefit from external knowledge even though they do not invest in innovation. Second, since by definition non-innovating firms do not invest in "frontier innovation" (innovations that push the technological frontier), the results suggest that such incumbents are most likely benefiting from "technological adaptation or imitation," which is aided by geographical proximity to R&D intensive firms operating in the same industry.

As far as inter-industrial external knowledge is concerned, the results suggest that the entrants do not benefit from the such external knowledge. And for incumbents, its estimated impact is not robust across methods. One reason for such results could be that our measure of external R&D knowledge is based on the geographical distance of the other firms in other industries; a measure based on "technological distance" as in Bloom *et al.* (2013) or a measure based on forward and backward linkages as in Pavlínek and Žžalová (2014) could have yielded different results.

Table 3: **Estimates of within and across industries regional knowledge spillovers**

	Incumbent				Entrant			
	FE	RE	ACF	OP	FE	RE	ACF	OP
log(Capital/Employees)	0.077***	0.113***	0.172***	0.170***	0.039	0.090***	0.155***	0.115***
	(0.011)	(0.007)	(0.004)	(0.006)	(0.030)	(0.017)	(0.030)	(0.007)
log(R&D/Employees)	0.007	0.008**	0.022***	0.042***	0.024*	0.026**	0.037**	0.017*
	(0.004)	(0.003)	(0.006)	(0.012)	(0.013)	(0.011)	(0.017)	(0.01)
log(Intra-industry R&D)×Innovating	0.011***	0.002	0.021**	-0.010	0.007	0.02	0.006	0.009
	(0.004)	(0.003)	(0.008)	(0.010)	(0.016)	(0.012)	(0.018)	(0.011)
log(Intra-industry R&D)× Non-Innovating	0.016**	0.008	0.054***	0.028***	-0.045*	-0.011	0.023	-0.016
	(0.008)	(0.006)	(0.004)	(0.006)	(0.025)	(0.019)	(0.025)	(0.011)
log(Inter-industry R&D)×Innovating	0.023	-0.001	0.003	0.030***	-0.006	0.002	-0.008	-0.015**
	(0.017)	(0.011)	(0.017)	(0.011)	(0.063)	(0.029)	(0.011)	(0.007)
log(Inter-industry R&D)× Non-Innovating	0.013	-0.006	-0.018***	0.033***	0.027	0.016	0.000	0.002
	(0.017)	(0.012)	(0.005)	(0.009)	(0.064)	(0.03)	(0.016)	(0.005)
No. of Observations	4414	4414	4414	4010	711	711	711	639

Note: Dependent variable is log(Value-Added/Employees) when employing ACF method and log(Revenue/Employees) when employing FE, RE, and OP methods. All specifications include log(Employees), Dummy for Zero R&D, Age of the firm, Dummy for North Estonia and Time and Industry Dummies. In addition, the FE, RE, and OP columns include log(Material/Employees).

Standard Errors in Parenthesis. Significance levels : $*$: 5% $**$: 1% $***$: 0.1%

5.2.2. *Inter- and Intra-Industrial Productivity spillovers*

A firm that operates in a region or market where other market participants display high levels of productivity can, through face-to-face contact as in Storper and Venables (2004), learn through observing productivity directly. This externality is distinct from the external knowledge spillover that other firms may have generated via R&D investments. Such productivity spillovers can take the form of measuring oneself against a competitive benchmark, understanding supply and production networks, or adopting best practices.

To assess the effect that spillovers from the productivity of other firms have on the productivity of entrants and incumbents, we calculate for each firm the average productivity of other firms within and outside of its own industry sector. To this end, we generate a variable that captures the leave-one-out weighted mean of labour productivity in each year and 2-digit NACE industry. These measures are then subsequently included in similar regression specifications as used for the analysis of R&D spillovers in section 5.3.1.

In Table 4 we present the results of estimating the differential impact of productivity spillovers for innovating and non-innovating firms. Again, for the purpose of exposition, in the table we include the coefficient estimates of only the average productivity of other firms within and outside of its own industry sector interacted with dummy variables for innovating and non-innovating firms in addition to the coefficient of the firm's own R&D expenses.

The OP, ACF and RE estimates suggest that incumbents are likely to benefit from geographical proximity to high performing firms from within their own sector. Moreover, the results indicate that for the incumbents, the impact of within industry productivity spillovers are even higher than the private returns to R&D. The ACF estimates, however, seem to suggest that non-innovating entrants are negatively affected by high intra-industry productivity spillovers. It therefore seems that other high productive enterprises geographically close to the non-innovating entrants increase their relative cost of operation. This could happen if, as argued in Nelson (1982) and Cohen and Levinthal (1989), certain entrants do not invest sufficiently in R&D and/or in building absorptive capacity while other entrants and established firms do take advantage of their own innovation or spillovers, which comes from purchasing productivity enhancing technology or adopting best practices. Thus, the "learning failure" of non-innovating entrants could increase their relative cost, resulting in lower value-added.

Coming to inter-industrial productivity spillovers, the FE and RE estimates suggest that there is no impact of inter-industrial productivity spillovers for either the entrants or the incumbents. On the other other hand, the OP and the ACF estimates seem to suggest the opposite impact for the incumbents. On the whole, the estimated impact of inter-industrial productivity spillovers is not robust across methods. This, again, could be due to the fact that our measure of external R&D knowledge is based on the geographical distance of the other firms in other industries. As suggested in the last subsection, a measure based on "technological distance" or one based on forward and backward linkages could yield different results.

Table 4: **Estimates of inter and intra-industry regional productivity spillovers**

	Incumbent				Entrant			
	FE	RE	ACF	OP	FE	RE	ACF	OP
log(Capital/Employees)	0.076***	0.114***	0.193***	0.106***	0.043	0.091***	0.140****	0.149***
	(0.011)	(0.007)	(0.001)	(0.024)	(0.030)	(0.017)	(0.028)	(0.031)
log(R&D/Employees)	0.007*	0.008**	0.016***	0.008	0.027**	0.030***	0.038***	0.055***
	(0.004)	(0.003)	(0.003)	(0.006)	(0.013)	(0.011)	(0.014)	(0.018)
log(Intra-industry Productivity)×Innovating	-0.008	0.047***	0.047***	0.062*	-0.041	0.027	-0.033	-0.004
	(0.016)	(0.011)	(0.002)	(0.033)	(0.054)	(0.035)	(0.033)	(0.033)
log(Intra-industry Productivity)× Non-Innovating	-0.039	0.073***	0.049***	0.113***	-0.091	0.012	-0.063***	-0.007
	(0.021)	(0.015)	(0.002)	(0.009)	(0.083)	(0.052)	(0.022)	(0.03)
log(Inter-industry Productivity)×Innovating	-0.045	0.004	0.014***	-0.002	-0.016	0.064	0.005	-0.045
	(0.040)	(0.023)	(0.001)	(0.011)	(0.138)	(0.064)	(0.023)	(0.044)
log(Inter-industry Productivity)× Non-Innovating	-0.023	-0.022	0.007***	-0.050***	0.039	0.079	0.043**	-0.032
	(0.042)	(0.025)	(0.001)	(0.023)	(0.145)	(0.073)	(0.020)	(0.046)
No. of Observations	4414	4414	4521	4147	711	711	720	657

Note: Dependent variable is log(Value-Added/Employees) when employing ACF method and log(Revenue/Employees) when employing FE, RE, and OP methods. All specifications include log(Employees), Dummy for Zero R&D, Age of the firm, Dummy for north Estonia and Time and Industry Dummies. In addition, the FE, RE, and OP columns include log(Material/Employees).

Standard Errors in Parenthesis. Significance levels : $*$: 5% $**$: 1% $***$: 0.1%

5.3. *Implication of Innovation for Productivity*

As it can be seen in Table 12, which has the descriptive statistics, less than 40% of the firm-years have positive R&D expenses, but about 75% of the firm-years in the sample have innovated to introduce at least one new product in the market or a new process. Also, about 7% of the firms that invested in R&D did not innovate a new product or process. These suggest that more firms innovate through the "doing, using and interacting" (DUI) mode of innovation rather than "scientific and technologically-based innovation" (STI) and that having positive R&D expenses is neither a necessary nor a sufficient condition for innovation.

Now, it has been found that firms in the low- and medium-tech sectors are usually engaged in the DUI mode of innovation while drawing on advanced science and technology results available through the distributed knowledge bases (Robertson *et al.*, 2009; Trott and Simms, 2017). Given that a large majority of the firm in our sample are in the low- and medium-tech manufacturing and less knowledge intensive services, and who innovate without formally engaging in R&D, focusing only on R&D will not provide an complete picture of the productivity implications of a firm's innovative activity.

Hence, to assess how innovation affects expected productivity, $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})$, across firms, we examine its distribution functions for the subsamples of observations with and without innovation. While the impact of innovation on productivity could differ depending on whether the firm innovated (a) in both time periods ($I_{j,t} = 1, I_{j,t-1} = 1$), (b) in the current time period ($I_{j,t} = 1, I_{j,t-1} = 0$), (c) in the last time period ($I_{j,t} = 0, I_{j,t-1} = 1$), (d) or did not innovate at all ($I_{j,t} = 0, I_{j,t-1} = 0$), here, we aggregate the impacts of (a), (b), and (c), and compare the aggregate productivity impact against the productivity of firms that did not innovate in the current and in the last period.

In Table 5, we present a description of the innovative activities of the incumbents and the entrants. Now, firms that innovate regularly or show persistence in innovative activity will have most likely innovated in both time periods, t and $t-1$. We find that in our sample, firms exhibit a high degree of persistence in innovative activity, but the persistence is higher among the incumbents (45.9%) compared to persistence among the entrants

TABLE 5

Description of innovative activity in the current, t, and the previous, $t-1$, periods

Incumbents				Entrants			
	$I_{j,t}=0$	$I_{j,t}=1$	Total		$I_{j,t}=0$	$I_{j,t}=1$	Total
$I_{j,t-1}=0$	935	1261	2196	$I_{j,t-1}=0$	142	260	402
	(20.45)	(27.57)	(48.02)		(19.48)	(35.67)	(55.14)
$I_{j,t-1}=1$	278	2099	2377	$I_{j,t-1}=1$	39	288	327
	6.08	(45.90)	(51.98)		(5.35)	(37.51)	(44.86)
Total	1213	3360	4573	Total	181	548	729
	(26.53)	(73.47)	(100.00)		(24.83)	(75.17)	(100.00)

Note: Cell percentage in parentheses.

(37.5%)[10]. Consequently, the major component in the aggregated impact will be the impact of innovation in both time periods.

To describe differences in expected productivity, $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})$, between firms that innovate and firms that do not, we employ kernels to estimate the distribution functions of $g(.)$ for the subsamples of incumbents and entrants with innovation in at least one time period and without any innovation. The expected productivity, $g(.)$, is estimated using the methodology in ACF as the option in STATA's 'prodest' to endogenize the evolution of ω_{jt} is available only when implementing the methodologies in ACF and LePe. Estimates of $g(.)$ obtained after estimating equation (4.9) are based on the specification in Table 3, in which intra- and inter-industry knowledge capital are interacted with dummies for innovating and non-innovating status. As all specifications gave the same conclusion regarding the impact of innovation on TFP, our choice of specification here is arbitrary.

Now, while STATA's 'prodest' command allows us to specify the arguments in $g(\omega_{j,t-1}, .)$, it does not give the estimates of $g(\omega_{j,t-1}, .)$. We therefore estimate the residual, $\omega_{j,t} + \epsilon_{jt}$, in equation (4.9) as a proxy for $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})$. This method of estimating total factor

[10]Though our estimation sample is highly unbalanced, primarily because balance sheet information was found to be missing for firms in the CIS data, but since in the raw CIS data there is high degree of overlap of the firms over the waves, we were able to garner information on innovative activity in the last period without losing many firms.

productivity (TFP) assumes that the coefficients are constant across entities, and is the one typically used by econometricians (Hall, 2011). Given that in equation (4.7) we defined ω_{jt} as $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})+\xi_{jt}$, the estimated residuals are the estimates of $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})+\xi_{jt}+\epsilon_{jt}$. Now, since the idiosyncratic errors, $\xi_{jt}+\epsilon_{jt}$, are independent of the covariates, $D^0_{jt}, l_{jt}, k_{jt}, r_{jt}$, and e_{jt}, in equation (4.9), and $I_{j,t}$ & $I_{j,t-1}$, besides having a mean of 0, any comparison between two groups of producers of the estimated density of the residuals will only reflect the differences in $g(\omega_{j,t-1}, I_{j,t}, I_{j,t-1})$ for the two groups [11]. In what follows, therefore, we refer to the estimated residuals as expected productivity, $g(.)$.

In Figure 1 we study the distribution of $g(.)$. In Figure 1a we plot the average of the estimated productivity, $g(.)$, for the incumbents and the entrants for each of the years. In the figure we see that the annual means of $g(.)$ for the incumbents and the entrants are relatively constant. This indicates that in our sample the distribution of $g(.)$ for the incumbents and the entrants does not change much over time. We can therefore pool the estimated $g(.)$ from all time periods and estimate its density for the incumbents and the entrants.

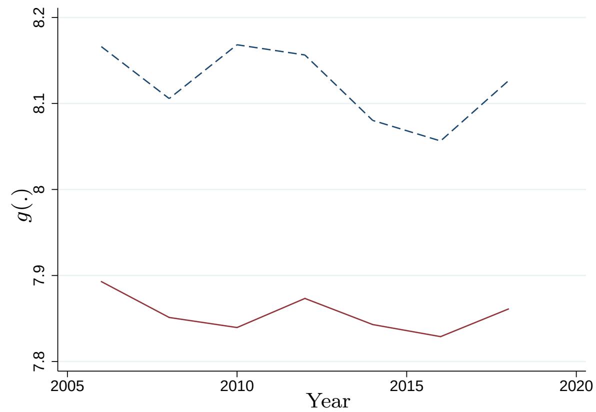
In Figure 1b we plot the estimated density of $g(.)$ for entrants and incumbents. We find that, on average, the expected productivity, $g(.)$, of the entrants is higher than that of the incumbents. Here we would like to note that the difference in average productivity of the entrants and the incumbents, which varied marginally across specifications, was found to be positive across specifications and both the control function methodologies, OP and ACF. This is in contrast to labour productivity, which on average is found to be somewhat higher among the incumbents than the entrants (see Table 12). This, as we know, could be possible because labour productivity can change due to changes in the capital-labour

[11] The prodest command does, however, give an estimate of ω_{jt} as

$$\hat{\phi}(D^0_{jt}, l_{jt}, k_{jt}, r_{jt}, e_{jt}) - [\hat{\beta}_0 + D^0_{jt}(\widehat{a_0 - \beta}_0 + \hat{\beta}^{0+}_l l_{jt} + \hat{\beta}^0_k k_{jt}) + (1 - D^0_{jt})(\hat{\beta}^+_l l_{jt} + \hat{\beta}_k k_{jt} + \hat{\beta}_r r_{jt}) + \hat{\beta}_e e_{jt}],$$

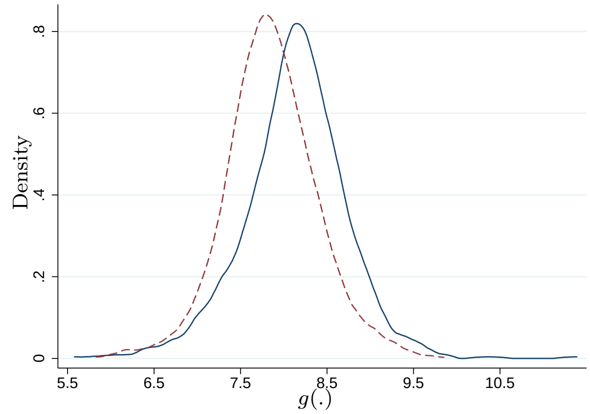
where $\phi(.)$, which is estimated in the first stage, is given by $\phi(D^0_{jt}, l_{jt}, k_{jt}, r_{jt}, e_{jt}) = [\beta_0 + D^0_{jt}(a_0 - \beta_0 + \beta^{0+}_l l_{jt} + \beta^0_k k_{jt}) + (1 - D^0_{jt})(\beta^+_l l_{jt} + \beta_k k_{jt} + \beta_r r_{jt}) + \beta_e e_{jt}] + f^{-1}_t(l_{jt}, k_{jt}, r_{jt}, e_{jt}, m_{jt})$; see assumption 5, where ω_{jt} has been defined as $f^{-1}_t(l_{jt}, k_{jt}, r_{jt}, e_{jt}, m_{jt})$. The distribution functions of the estimated ω_{jt} for the subsamples of incumbents and entrants with and without innovations are quite similar to the distribution functions of the estimates of $g(.)$ that have been plotted here.

ratio without any changes in technology. That is, change in labour productivity could be due to changes in technology or changes in factor accumulation.



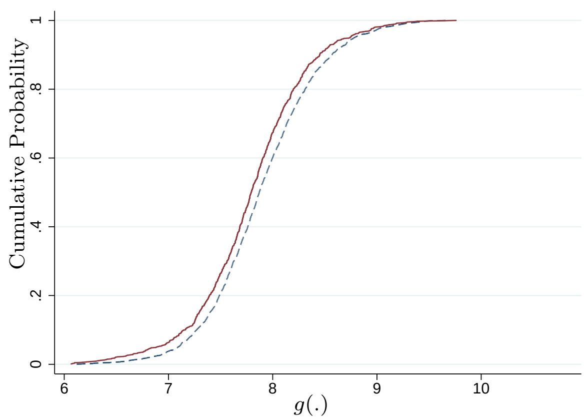
Incumbents: —— , Entrants: - - -

(a) Year-wise average $g(.)$



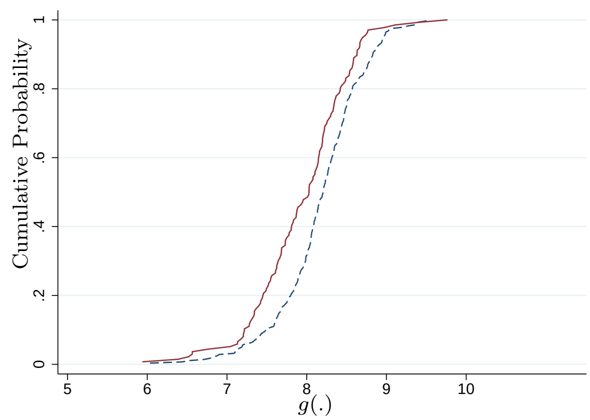
Incumbents: —— , Entrants: - - -

(b) Density plots of $g(.)$



Innovators: - - - , Non-Innovators ——

(c) Distribution of $g(.)$ for innovators & non-innovators among incumbents



Innovators: - - - , Non-Innovators ——

(d) Distribution of $g(.)$ for innovators & non-innovators among entrants

Figure 1: **Distribution of expected productivity,** $g(.)$**, which depends on current and past innovation,** $I_{j,t}$ **&** $I_{j,t-1}$

Thus higher labour productivity among the incumbents could be due to higher capital accumulation by the incumbents. TFP, on the other hand, measures firm ability or efficiency, such as managerial talent, quality of inputs, innovation, etc., that are not accounted for by the observed inputs (see Syverson, 2011). From figures 1a and 1b, we can conclude that, on average, entrants are more productive in their TFP than the incumbents. The fact that surviving young firms have above average productivity and that they grow faster than their mature counterparts, has been documented elsewhere (Foster *et al.*, 2006; Haltiwanger *et al.*, 2013).

Also, we find that estimated productivity is more dispersed among the entrants. Many studies have documented a higher dispersion of productivity among young firms. As discussed in Haltiwanger *et al.* (2013), young firms exhibit an "up or out" dynamic – they either grow fast on average or they exit. These "up or out" dynamics imply that exiting young firms have very low productivity while surviving young firms have above average productivity. This could potentially explain why productivity is more dispersed among the entrants[12]. Related to the "up or out" dynamics, Foster *et al.* (2018) explain that entry is associated "experimentation," which results high degree of within-industry productivity dispersion. Following this experimentation phase is the "shakeout" period, in which entrepreneurs that successfully innovate and/or adopt grow while unsuccessful entrepreneurs contract and exit yielding productivity growth. Foster *et al.* (2018) discuss a variety of mechanisms which can help understand how "experimentation" can generate heterogeneity in the factors that cause dispersion.

In Figure 1c, we plot the estimated cumulative density of $g(.)$ for innovators and non-innovators among incumbents. The estimated cumulative density of $g(.)$ for innovators and non-innovators among entrants can be seen in Figure 1d. We also apply the Kolmogorov-Smirnov test to compare the distribution of expected productivity for innovators and non-innovators. In Table 6 we test for the equality of the distributions for innovators and non-innovators.

In Figure 1c and Figure 1d, we see that the distribution function for innovators, among incumbents as well as the entrants, is to the right of the distribution function for non-innovators. This strongly suggests that the distribution function for innovators stochasti-

[12] Haltiwanger *et al.* (2013) state that this dynamic is an important feature of market based economies and is consistent with predictions in models of market selection and learning and models where it takes time for firms to build up their customer base or reputation in credit markets.

cally dominates the distribution function for the non-innovators. In Table 6, we reject the hypothesis for both groups of producers, incumbents and entrants, that the distributions of $g(.)$ for the innovators and the non-innovators are equal. Moreover, for both the incumbents and the entrants, the stochastic dominance of the distribution function for innovators over non-innovators could not be rejected.

TABLE 6

Kolmogorov-Smirnov Test for Equality of Innovators' and Non-Innovators' distribution of expected productivity

	Hypothesis	Test Stat.	p value
Incumbents	Expected productivity estimates for the innovators are larger than that for the non-innovators.	-0.002	0.994
	Innovators and non-innovators' have the same distribution of expected productivity.	0.067	0.004
Entrants	Expected productivity estimates for the innovators are larger than that for the non-innovators.	-0.007	0.988
	Innovators and non-innovators have the same distribution of expected productivity.	0.194	0.001

Also, as can be seen in Table 7, for both the entrants and the incumbents, the hypothesis that the average $g(.)$ for innovators and non-innovators is equal has been rejected. Moreover, we find that the difference in the average $g(.)$ of innovators and non-innovators for entrants is 0.22, which is much larger than for the incumbents for whom the difference is 0.07. These differences, however, are in logarithmic scale; at the mean, this difference in linear scale implies that an entrant who innovates is roughly 25% more productive than an entrant who does not. For the incumbents, it implies that, on average, a firm that innovates is 7% more productive than the one which does not. This suggests that entrants are more able to translate their innovations into productivity gains than the incumbents. Given that a higher percentage of entrants, 37%, compared to incumbents, 31%, reported product innovation, it suggests that entrants are more likely to make productivity gains by widening their spectrum of final goods or intermediate inputs and/or by establishing niche markets, and that the product innovations of the entrants yield greater rewards than that of the

TABLE 7

Test of Equality of Average $g(.)$ between Innovators and Non-Innovators

		Difference in average $g(.)$ of Innovators and Non-Innovators	$\Pr(\lvert T\rvert > \lvert t\rvert)$
When $g(.)$ depends on innovation indicators, $I_{j,t}$ & $I_{j,t-1}$.	Incumbents	0.068	0.000
	Entrants	0.220	0.000

The two sample t-test assumed unequal variances.

incumbents. Overall, this result is consistent with the results in section 5.1, where we found that, on average, entrants can increase their labour productivity more than the incumbents by investing an additional 1% in R&D.

5.4. *Comparison with Estimates for Germany*

In this section, we compare estimated elasticities of productivity with respect to own R&D and capital stock with those estimated in Lubczyk and Peters (2020)(LP). In Table 8 below, Baseline Specification refers to the specification in Table 4 in LP the specification in Table 2 in our paper. In Table 2, we had interacted the inputs, labour, capital and materials, with dummies for positive and zero R&D. Since the estimated elasticities for the two regimes did not turn out to be significantly different, for the purpose of comparison LP, we re-estimated the specification in Table 2 without interacting the inputs with the dummies. Specification with R&D Spillovers in Table 8 is the specification in Table 3 in our paper and Table 8 in LP, and Specification with Productivity Spillover refers to the specification in Table 4 in our paper and Table 11 in LP.

As can be seen from the table, the elasticities of productivity with respect to own R&D for Estonia are lower than those for Germany even though our estimates using the OP method vary considerably across specifications. This suggests that the German firms, both entrants and incumbents, on average, have a higher capacity to translate R&D into productivity gains compared to Estonian firms.

Now, previous studies at the industry level (mainly on manufacturing industries) clearly suggest a greater impact of R&D investment on productivity in the high-tech industries rather than in the low-tech ones (see Castellani *et al.*, 2019, and the references therein). In

TABLE 8

Comparing Elasticity of Productivity with respect to Own R&D and Capital with those obtained for Germany

	Germany				Estonia			
	OP		ACF		OP		ACF	
	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.
	log(R&D/Employees)							
Baseline Specification	0.024***	0.029***	0.057***	0.125***	0.015*	0.043*	0.019***	0.052***
	(0.004)	(0.010)	(0.002)	(0.002)	(0.009)	(0.022)	(0.003)	(0.018)
Specification with	0.022***	0.026***	0.050***	0.120***	0.042***	0.017*	0.022***	0.037**
R&D Spillover	(0.002)	(0.009)	(0.002)	(0.003)	(0.012)	(0.01)	(0.006)	(0.017)
Specification with	0.008***	0.024**	0.041***	0.117***	0.008	0.055***	0.016***	0.038***
Productivity Spillover	(0.002)	(0.010)	(0.002)	(0.002)	(0.006)	(0.018)	(0.003)	(0.014)
	log(Capital/Employees)							
Baseline Specification	0.076***	0.147***	0.127***	0.281***	0.136***	0.148***	0.196***	0.140***
	(0.026)	(0.029)	(0.000)	(0.001)	(0.027)	(0.036)	(0.001)	(0.027)
Specification with	0.021	0.148***	0.133***	0.255***	0.170***	0.115***	0.172***	0.155***
R&D Spillover	(0.026)	(0.007)	(0.002)	(0.003)	(0.006)	(0.007)	(0.004)	(0.030)
Specification with	0.035***	0.128***	0.183***	0.248***	0.106***	0.149***	0.193***	0.140****
Productivity Spillover	(0.008)	(0.038)	(0.004)	(0.001)	(0.024)	(0.031)	(0.001)	(0.028)

Standard Errors in Parenthesis. Significance levels : $*$: 5% $**$: 1% $***$: 0.1%

our sample less than 40% of the firm-years have positive R&D, which is mostly concentrated in high-tech manufacturing and knowledge-intensive services (Eurostat classification). However, the high-tech manufacturing constitute less than 3% of the total firm-year observations and the medium-high-tech constitute about 11%. These figures are much lower than the corresponding EU averages of 12.5% and 32% respectively (see European Commission, 2011, p. 121). Therefore, the estimated lower elasticities for Estonia could be due to the industry composition effect: Estonian firms in the aggregate exhibit a lower elasticity of productivity to R&D just because they have a lower percentage of firms in the high-tech industries, where the returns to R&D have revealed to be higher.

Interestingly, in our data, knowledge-intensive services constitute about 15% of the firm-year observations, which is high compared to EU average (see European Commission, 2013,

p. 292, which reports a simlar finding). However, as we found in our data, fewer firms in knowledge-intensive services introduced innovations, products and/or processes, as compared to the firms in the high-tech and the medium-high-tech manufacturing.

Ortega-Argilés *et al.* (2014, 2015) find that in traditional low-tech industries, which focus on process innovation, productivity gains turn out to be more related to capital accumulation rather than to R&D expenditures. Supporting this argument, Castellani *et al.* (2019) point out that complex and radical product innovation generally relies on formal R&D, while process innovation is much more related to embodied technological change achieved by investment in new machinery and equipment (see also Parisi *et al.*, 2006, who first reported the finding).

Now, what we find in our data is that (i) 47% of the firm-year observations are from low-tech and medium-low-tech manufacturing, while 23% of the firm-year observations are from less knowledge intensive services. (ii) Process innovation (40% of the firm-year observations) is more prevalent than product innovation (32%); even in high-tech and medium-high-tech manufacturing a higher percentage compared to low-tech manufacturing and all services engage in process innovation. Coupled with the fact that productivity gains from capital accumulation is higher than R&D expenditures – in fact, for incumbents it is higher than productivity gains from capital in Germany – the two facts, (i) & (ii), suggest that embodied technological change through capital accumulation, which is more likely to aid process innovation, has been more effective in generating productivity growth (Parisi *et al.*, 2006). This is also symptomatic of Estonian firms' distance from the technological frontier; when firms are at a distance from the technological frontier, R&D, besides generating productivity growth through innovation, facilitates technology transfer through learning and building up absorptive capacity (Cohen and Levinthal, 1989; Griffith *et al.*, 2004).

Bruno *et al.* (2019) point that the EU is the world region with the highest share of intra-regional trade (in our data, the majority of firms, 69%, have imported). On this basis, one should expect that trade and services flows are accompanied by technological knowledge flows. That is, imported machinery and equipment embody R&D and technological knowledge. To further support the claim that Estonian firms have mainly relied on embodied technological change by investing in new machinery and equipment, which are mostly im-

TABLE 9

Productivity Effects of Capital Accumulation for Importers and Non-Importers among Entrants and Incumbents

	Incumbent		Entrant	
	ACF	OP	ACF	OP
log(Capital/Employees) × Import Dummy	0.190***	0.139***	0.161***	0.150***
	(0.006)	(0.003)	(0.027)	(0.020)
log(Capital/Employees)× (1-Import Dummy)	0.176***	0.119***	0.109***	0.121***
	(0.002)	(0.009)	(0.024)	(0.016)

Note: Dependent Variables: log(Value-Added/Employees) when employing ACF and log(Revenue/Employees) when employing OP. All specifications include log(Employees), log(R&D/Employees) Dummy for Zero R&D, Import Dummy, Age of the firm, Dummy for North Estonia and Time and Industry Dummies. In addition, the OP columns include log(Material/Employees).

ported, to improve their productivity, in Table 9 we interact log(Capital/Employees) with the import dummy, which takes the value 1 if the value of imports in the firm-year was positive and 0 otherwise. As can be seen from the Table, the elasticity of productivity with respect to capital is higher – and significantly – for the firms that have imported than those that have not.

A vast amount of literature has focused on (1) complementarity between R&D investments and endowment in human capital endowment with appropriate HRM (Human Resource Management) practices, and (2) how organizational settings and strategic managerial practices are crucial in affecting productivity trends (Fagerberg *et al.*, 2010; Castellani *et al.*, 2019). Given data limitations, which prevent us to directly investigate whether a difference in human capital endowment and managerial gap can explain the relative inability of Estonian firms to translate R&D efforts into productivity gains, this is left for future research. Other technological and social capabilities, whose lack could restrict both R&D activities as well as the efficiency of R&D include the institutional environment (corruption, law and order, independence of courts, property rights, business friendly regulation, government preferential policy), social values (civic activities, trust, tolerance, religious ethics, attitudes towards technology and science), and the financial system (Fagerberg *et al.*, 2010; Aghion *et al.*, 2011). It would be worthwhile measuring the difference in institutional environment/quality of governance, social values, and level of financial development to see if these can explain the relative inability of Estonian firms to translate R&D efforts into productivity gains.

6. CONCLUDING REMARKS

A large proportion of productivity growth, which as we know is the key driver of economic growth, is due to reallocation emanating from the entry and exit of firms. First, since this reallocation is tied to the heterogeneous productivity impacts of R&D investment and innovation undertaken by incumbents and entrants, in this paper we study the productivity implications of R&D and innovation for incumbents and entrants. More precisely, we investigate how the elasticity of productivity with respect to R&D investment differ between entrants and incumbents. Second, we study how much entrants and incumbents learn and benefit from knowledge produced outside the firm boundaries. Third, since R&D investment provides only a partial picture of the innovation activities in a firm, we also look at how innovation outputs, not all of which result from R&D investment, affect the productivity of these two groups of producers. Finally, since catching up economies tend to grow more on imitation activities, with R&D also facilitating in building absorptive capacity, embodied technological change through capital accumulation is likely to have a significant productivity impact. We, therefore, study the productivity impact of capital accumulation for the incumbents and the entrants.

We used seven waves of Estonian Community Innovation Survey (CIS) data for the study. Certain information needed from the firms' balance sheets was obtained from the Estonian Business Registry data, which is census data; missing information, if available, was obtained from EKOMAR data, which is survey data.

Several interesting conclusions emerge from our analysis. First, while both entrants and incumbents gain significantly from investing in R&D, we find a robust result that the average elasticity of labour productivity for entrants with respect to R&D investment exceeds that of the incumbents. Second, entrants, on average, have higher total factor productivity (TFP) than incumbents and are more heterogeneous in their TFP than incumbents. Third, the average difference in TFP between innovators and non-innovators is much higher for the entrants (25%) than for the incumbents (7%). These results suggest that Estonian entrants, as elsewhere, are more able to translate their R&D and innovative efforts into productivity gains compared to incumbents.

Fourth & Fifth, comparing our results to those in Lubczyk and Peters (2020), we find that German firms on average have a higher capacity to translate their R&D activities into productivity gains compared to Estonian firms. However, we find that productivity elasticity with respect to capital is higher than with respect to R&D; in fact, for Estonian incumbents it is higher than their German counterparts. This suggests that in Estonia, embodied technological change through capital accumulation has been more effective in generating productivity growth than R&D expenditure.

Sixth, in results related to spillover effects, it is mostly the incumbents who benefit from within-industry knowledge that is generated by other firms situated in close proximity. Seventh, incumbents are likely to become more productive when other firms in close proximity display higher average productivity. Eighth, both knowledge and productivity spillovers seem to be higher for the non-innovating compared to the innovating firms.

There are certain limitations in our paper, which are primarily due to lack of data. First, as Community Innovation Surveys (CIS) consider firms with at least 10 employees, the entrants included in these data may not be representative of the population of newly born firms, which are unlikely to exceed this threshold in the first years of their existence. Relying on CIS data could therefore limit the number of newly established firms. Second, in estimating between-industry knowledge and productivity spillovers, we have not differentiated with regard to the degree in which different industries are more or less distant from another in the technology space. Moreover, the spillover potential between industries may differ depending on whether firms in different industries produce complementary or substitute goods. Measures of external knowledge produced in other industries that are based on technological distance between firms and/or forward and backward linkages between industries could have yielded different results for the between-industry spillover effects.

Notwithstanding certain limitations, our analysis yields results that have policy implications. The finding that R&D and innovations benefit entrants disproportionately more than the incumbents points to the profound impact entry can have on economic dynamics. It also emphasises the additional benefits there may be from innovative entrepreneurship.

The result of positive R&D and productivity spillovers between firms located in proximity suggests that industrial policy making should take agglomeration economics into account. Finally, since Estonia, a CEE country, is yet to close its gaps with the technological frontiers, policies need to prioritise improvements in the country's absorptive capacity.

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APPENDIX A: TABLES AND FIGURES

Table 10: **Summary Statistics**

	2006		2008		2010		2012		2014		2016		2018	
	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.
log(No. of Employees)	3.98	4.17	3.73	3.98	3.84	4.1	3.97	4.15	3.87	4.15	3.69	3.91	3.67	3.84
log(Capital)	13.2	13.46	12.96	13.5	13.01	13.85	12.75	14.15	12.74	14.03	12.81	13.72	12.73	13.78
log(Material Cost)	13.39	13.59	12.79	13.01	13.05	13.41	13.26	13.77	13.37	13.66	13.09	13.19	13.37	14.36
log(Investment in Fixed Assets)	12.11	12.16	11.31	11.6	11.44	11.61	11.48	12.23	11.75	12.21	11.23	11.74	10.35	11.04
log(R&D Expenditure)	5.96	6.04	5.95	6.2	3.67	3.71	11.32	10.84	11.1	11.2	11.25	11.03	10.5	10.93
Dummy for Positive R&D	0.26	0.36	0.21	0.24	0.26	0.32	0.5	0.42	0.41	0.36	0.29	0.24	0.41	0.42
Age	6.3	13.72	5.96	15.01	5.87	16.37	6.05	17.76	5.81	19.11	6.11	20.37	6	21.6
log(Value-Added)	13.1	14.06	13.69	11.03	13.91	14.1	13.93	14.32	13.97	14.37	13.63	14.09	14.02	14.3
log(Gross Output)	15.21	15.24	14.77	15.01	15.08	15.24	14.85	15.51	15.01	15.42	14.73	15.12	14.66	15.16
Dummy for Innovative	0.99	0.99	0.65	0.64	0.78	0.83	0.94	0.97	0.78	0.70	0.69	0.65	0.93	0.90
Dummy for Innovator	0.96	0.96	0.63	0.61	0.71	0.77	0.89	0.89	0.68	0.63	0.69	0.62	0.78	0.82
Dummy for North	0.54	0.52	0.59	0.51	0.6	0.52	0.46	0.52	0.61	0.53	0.63	0.5	0.74	0.52
log(Intra-Industry R&D)	6.97	6.78	7.36	6.94	5.01	4.48	12.23	11.59	11.51	11.07	11.99	11.4	11.47	10.86
log(Inter-Industry R&D)	12.06	11.89	12.51	12.17	10.11	9.79	16.7	16.99	17.16	16.89	17.59	17.01	17.64	16.69
No. of Firms	143	637	212	1089	112	703	78	479	57	439	100	884	27	342

Table 11: **Summary Statistics of some variables Scaled by No. of Employees**

	2006		2008		2010		2012		2014		2016		2018	
	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.	Ent.	Inc.
log(Value-Added)	10.01	9.89	9.94	9.87	10.07	10.01	9.96	10.17	10.10	10.22	9.93	10.18	10.35	10.45
log(Gross Output)	11.22	11.07	11.04	11.03	11.24	11.16	10.88	11.35	11.14	11.27	11.04	11.21	10.99	11.32
log(Capital)	9.21	9.29	9.23	9.5	9.16	9.77	8.79	9.99	8.87	9.88	9.12	9.81	9.05	9.93
log(Material Cost)	9.71	9.42	9.05	9.03	9.21	9.32	9.29	9.62	9.51	9.51	9.41	9.27	9.69	10.51
log(R&D Expenditure)	1.74	1.68	1.76	1.76	-0.36	-0.6	7.28	6.55	7.07	6.76	6.37	6.69	6.17	6.66
log(Intra-Industry R&D)	2.49	2.46	2.77	2.33	0.46	-0.003	7.66	7.05	6.96	6.36	7.41	6.61	7.34	6.8
log(Inter-Industry R&D)	7.54	7.42	7.8	7.53	5.29	5.07	12.39	12.52	12.42	12.23	13.17	12.63	13.28	12.42
log(Intra-Industry Value-Added Labor Productivity)	8.26	8.03	8.47	8.19	8.72	8.38	8.36	8.5	8.4	8.34	8.53	8.2	9.27	8.73
log(Inter-Industry Value-Added Labor Productivity)	8.38	8.3	8.55	8.25	8.88	8.6	8.67	8.74	8.65	8.41	8.75	8.31	9.21	8.55
log(Intra-Industry Gross Output Labor Productivity)	9.66	9.52	10.08	9.72	10.19	9.94	9.99	10.09	9.91	9.74	10.25	9.75	10.09	9.84
log(Inter-Industry Gross Output Labor Productivity)	10.05	9.92	10.91	10.48	10.99	10.75	10.96	10.89	10.78	10.31	10.3	9.82	10.25	9.76

TABLE 12

Test of Equality of Means between Entrants and Incumbents

	Entrants	Incumbents	Difference	$\Pr(\|T\| > \|t\|)$
log(Value-Added Productivity)	10.01	10.07	-0.06	0.043
log(Gross Output Productivity)	11.09	11.17	-0.07	0.045
log(No. of Employees)	3.83	4.03	-0.20	0.00
log(Capital)	9.12	9.7	-0.60	0.00
log(Material Cost)	9.34	9.39	-0.06	0.41
log(Investment in Fixed Assets)	11.52	11.83	-0.30	0.00
R&D Expenditure	159,473	79,014	80,459	0.11
Dummy for Positive R&D Expenditure	0.37	0.40	-0.03	0.11
Dummy for Innovator	0.75	0.73	0.02	0.33
Dummy for North	0.58	0.51	0.06	0.00
Intra-Industry log(R&D/No. of Employees)	4.01	4.01	-0.006	0.96
Inter-Industry log(R&D/No. of Employees)	9.12	9.43	-0.31	0.03
Intra-Industry log(Value-Added Productivity)	8.49	8.28	0.2	0.003
Inter-Industry log(Value-Added Productivity)	8.62	8.43	0.22	0.00

The two sample t-test assumed unequal variances.