Working Paper

Incumbents and Entrants as Carriers of Innovation and Productivity Growth

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11/2020 May

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 822781

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May 7, 2020

Abstract

This paper compares the role of innovation on productivity growth for entrants and incumbents. Creating a novel representative micro data set for both groups of firms in Germany, we find that entrants experience significantly larger gains from investments in R&D than incumbents. Entrants' returns to innovation are also considerably more heterogeneous, with output elasticities ranging from -4.5 to 12.4% along the conditional productivity distribution, while incumbents' benefits are in a fairly small bandwidth of 1.4 to 3.4%. Finally, our findings reveal differential learning effects of entrants and incumbents from knowledge that is produced outside their own firm boundaries. Both entrants and incumbents benefit from regional spillover effects within and across industry sectors. Within industries, these spillovers seem to mainly be driven by aggregate productivity but we also provide evidence of incumbents learning from entrants' R&D investments.

Keywords: R&D, productivity growth, entrants, incumbents, spillovers

JEL Classification: O31, O32

* **Acknowledgments**: This paper is an outcome of the GrowInPro project which was funded by the European Commission, Research Directorate General as part of the European Union Horizon 2020 Research and Innovation Action under grant agreement No 822781. Further details can be found at: www.growinpro.eu

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1 Introduction

Firm-level productivity, the rate at which a firm is able to transform inputs into outputs, is a key indicator of competitiveness and economic performance. The most productive firms will be able to position themselves most efficiently in a competitive market and as such will be able to increase market shares and yield profits. Similarly, an economy with high aggregate productivity has better chances of being well positioned in the global competition and of achieving higher economic growth.

Prior literature has impressively shown that firm-level productivity is closely linked to innovation as the central key to improving firm performance (for recent surveys see Hall, Mairesse, and Mohnen 2010; Hall 2011; Mohnen and Hall 2013). Firms investing in innovation do so in order to become more productive, increase their output and thereby improve their profits relative to their competitors.

In this paper, we study and compare the role innovation plays for driving productivity for two important groups of firms in the economy: entrants and incumbents. The underlying research questions is whether and to what extent the linkage between innovation and productivity is contingent on how long a firm has been in the market. More explicitly, creating a unique novel data base that is representative for both groups, we will compare entrants – defined as firms that are new to the market and have been active for up to eight years – and incumbents – firms that are established in the market and have been active for more than eight years – with regards to how much they benefit from own investments in R&D in terms of productivity improvements but also how much they can learn and benefit from R&D done by other entering or incumbent firms.

By looking at entrants and incumbents, we focus on two very different groups of firms. On the one hand, entrants are new to the market and in many ways still need to learn about the economic environment in which they operate. On the other hand, incumbents have accumulated considerable experience in their competitive environment and command well established capabilities. In this context, innovation may have a very different meaning for entrants or incumbents. As entrants are often resource-constrained, committing a sizeable part of the limited resource endowment to uncertain R&D activities can constitute a significant business risk. Limits to firm size, staff experience and organizational structure may create further complications for the innovation process, especially when unforeseen circumstances arise. At the same time, successful innovation 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 2012). Thus, while one would expect the impact of R&D spending on productivity to be volatile to some extent for new entrants, the situation is quite different for incumbents. Given their longer track record of established market participation, they are presumably better prepared for innovative activity. Although they commonly lack the organizational agility of smaller and younger competitors, they may compensate for this with existing resources, business experience and innovation capacity. While start-ups need to establish a business in the first place, an incumbent can build on its existing infrastructure. On the one hand, the existing business experience and infrastructure may enable the incumbent to pursue more ambitious R&D projects. Moreover, the experience of having conducted successful innovation in the past is increasing the likelihood of future innovation (Peters 2009; Raymond, Mohnen, Palm, and van der Loeff 2010; Le Bas and Scellato 2014) and may help such organizations to achieve higher levels of efficiency in carrying out their R&D activities (Lööf and Johansson 2013). On the other hand, as incumbents already have established products and production technologies in place, their innovative activity is therefore more often of an rather incremental nature, as they want to safeguard their existing profits and avoid the burden of organizational restructuring, which is often associated with radical innovation. By contrast, young firms are more inclined to exploit new ideas and are therefore more often seen as the root of radical innovation (Veugelers 2008).

Prior evidence on the link between innovation and productivity has mainly focused on incumbent firms. Up to now, there is only limited evidence on how this relationship is contingent on firm age (Huergo and Jaumandreu 2004a; Coad, Segarra, and Teruel 2016). One problem with existing studies, however, is that the underlying data are often restricted to firms with at least 10 or 20 employees, which naturally limits the number of newly established firms, as only a very small proportion of entrants exceeds this threshold in the first years of their existence.[1] The entrants included in these data cannot be seen as being representative for the population of newly born firms.[2]

In this paper, we create a novel firm-level panel data set by merging two existing micro data sets, the Mannheim Innovation Panel (MIP) and the IAB/ZEW Start-Up Panel (MSP). This yields a representative data set for the population of newly born and incumbent firms in Germany for the period 2005-2017, and it provides us with comparable information on firm's R&D activities, financial development, and information required to generate productivity measures. Our empirical analysis is led by answering three research questions surrounding the relationship of innovation, productivity and firm age. First, do entrants benefit more from investing in own R&D activities than incumbent firms? Second, is the heterogeneity in the returns to own R&D larger for entrants than for incumbent firms? And finally, do we observe a differential learning of entrants and incumbents from knowledge that is produced outside their own firm boundaries and if so from whom do entrants and incumbents learn?

Our analysis shows six major findings. First, we find a robust positive and significant impact of investing in own R&D on productivity for both entrants and incumbents.

[1] Community Innovation Survey (CIS) and R&D survey data are the most commonly used data. The target population of CIS only includes firms with 10 or more employees. According to the Frascati manual of the OECD, the target population of the R&D survey consists of all R&D doing firms, however this information is often not available for newly born firms, resulting in a severe under-representation of newly established firms (OECD 2015).

[2] For example, in the study of Coad, Segarra, and Teruel (2016) the average number of employees among young firms (less than 10 years) is 96.7 for R&D firms and 128.9 for non-R&D firms. Huergo and Jaumandreu (2004a) do not report average firm size by firm age but their sample only includes firms with 10 or more persons employed.

Second, the average return to innovation for entrants significantly exceeds the return for incumbents. Third, firm-level heterogeneity in the returns to innovation is larger for entrants. Entering firms at the lower buttom of the productivity distribution fail to benefit from investing in R&D while at higher quantiles of the distribution entrants experience disproportionately high and increasing returns to innovation, resulting in output elasticities that range from -4.5 to 12.4%. In contrast, incumbents benefit from innovation in a relatively narrow range of 1.4 to 3.4% along all quantiles of the conditional productivity distribution. Fourth, both entrants and incumbents benefit from knowledge that is generated by other firms in the same region. We find these effects to hold both within and across industry sectors. Fifth, while positive and significant for both, entrants on average benefit more from spillovers within industrial sectors while incumbents benefit more from the activities from firms in different industries. Sixth, finally, in examining whether these spillovers themselves originate from entrants or incumbents, we show that the productivity of entrants in particular is positively affected by learning from other productive entrants. We also find evidence of positive spillovers from entrants' R&D investment on incumbents' productivity in the same region and industry.

The remainder of this paper is structured as follows. Section 2 discusses the relationship between firm age, innovation and productivity. Section 3 briefly explains the empirical framework used and section 4 describes the data of our study. Section 5 presents and discusses the our empirical results while section 6 draws concluding remarks.

2 Literature

Understanding productivity and its determinants has been a focal point of economic research for much of the last century. In this context, there has been a long-standing discussion on how different firms contribute to productivity and productivity growth. In particular, scholars have studied how dynamics between entrants and incumbents impact aggregate productivity development, highlighting both differential and interrelated effects.

Early studies have shown that incumbents may enjoy inherent advantages in production efficiency. In contrast to their competitors that are new in the market, the established firms have better access to technology and often display higher learning capabilities. Moreover, incumbents are often in a more secure position allowing them to successfully navigate business and other uncertainties. Part of the explanation for why incumbents may outperform entrants, however, lies in selection. Only firms which earn sufficiently large profits to justify continuing operations stay in the market, meaning that only sufficiently productive entrants ever become incumbent in the first place (Nelson and Winter 1982; Jovanovic 1982; Hopenhayn 1992; Ericson and Pakes 1995).

Most entrants are small and small firms may generally have efficiency advantages over incumbents due to their organizational design. They tend to possess more flexible and non-hierarchical organizational structures. As such, they can be better set up to react to changing competitive pressures and market conditions, an advantage that is particularly important with regards to innovative activity (Audretsch 2002).

Adaptation to the competitive environment is a key determinant of an entrant's chances to successfully participate in a market. In particular, entrants study and assess the market conditions surrounding them as well as the behavior of other market participants. This learning process allows entrants both to adjust their capabilities and strategic orientation and to benchmark their performance against market incumbents (Taymaz 2005; Coad, Segarra, and Teruel 2016).

This process of market entry, and potentially subsequent exit, contributes to what is commonly referred to as business dynamism. Entry and exit from a market is a key mechanism through which the firm population changes and through which productive resources may be reallocated. In this context, young firms have been show to for instance make substantial contributions to job growth in the economy (Decker, Haltiwanger, Jarmin, and Miranda 2014). At the same time, studies have shown that this dynamic has been slowing down in recent years with both the share of economic activity attributable to newly founded firms as well as firm entry rate decreasing over time (Akcigit and Ates 2019a,b; Gourio, Messer, and Siemer 2014). An important aspect of young firms' contributions to aggregate growth and productivity is the role of heterogeneity. Entry and subsequent exit dynamics have been attributed to 'up or out' competition provided by competitive entrants. Both incumbents and less productive entrants may find themselves knocked out of contention by very productive start-ups (Haltiwanger 2012). Decker, Haltiwanger, Jarmin, and Miranda (2014) also document considerable heterogeneity in the contributions entering firms make to growth and show that most of the positive growth effects stem from the upper parts of the distribution.

Theoretically, many of these results build upon firm entry (and exit) being a choice based on the potential entrant's productivity level. The firm decides to participate in the market based on its estimated productivity level relative to the productivity level of its eventual competitors. Only if productivity is sufficiently high for the firm to expect positive economic profits, entry will be worthwhile. Theoretical approaches, such as Syverson (2011), frequently model this entry decision process as firms drawing from a productivity distribution and then comparing their draw to the population of firms already in the market. If productivity is sufficient to enter the market, the firm will do so. By construction, the productivity of firms that decide to enter the market will thus often be higher than the productivity of firms that decide to leave the market. This also implies that, generally, new entrants may find themselves on average to be positioned in the upper part of the overall productivity distribution in the market. As the market evolves, more firms enter and the order of firms in the productivity distribution changes. This may carry with it implications for the allocative efficiency of resources among firms competing in the market. Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018) model these dynamics in a theoretical framework where firms are of a high- and a low-quality type. Firms that enter the market are disproportionately of high-quality type but may become low-quality firms with a certain transition probability over time. As such, a once efficient allocation of resources may become inefficient as more productive new entrants make better use of production inputs.

Existing research has documented some of these theoretical insights empirically. Foster, Haltiwanger, and Krizan (2006) show that, indeed, the total factor productivity of entrants is higher than the productivity of incumbent firms. Similarly, Foster, Haltiwanger, and Syverson (2008) document that the productivity of firms joining the market anew is on average higher than the productivity of the firms that are leaving the market. Foster, Haltiwanger, and Syverson (2008) argue that the productivity advantages of entrants' vis-à-vis incumbents may even be understated due to differences in pricing between established firms and newly joining ones. As such, both productivity differences as well as differences in mark-ups may play a role. However, some studies also show that entrants may start with productivity lower than that of incumbent firms (Jensen, McGuckin, and Stiroh 2001; Coad, Segarra, and Teruel 2013, 2016).

A key contribution of this paper is to better understand the role that innovation plays in determining the relative contributions to aggregate productivity from young and incumbent firms. While Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018) go some way in establishing this link by theoretically and empirically analyzing the transition of high-quality firms to low-quality firms, relatively little scholarly research has assessed these dynamics with firm-level empirical applications. A notable exception is Huergo and Jaumandreu (2004a) who show that entering firms experience above-average productivity growth that converges over time. Process innovation reinforces productivity gains. Huergo and Jaumandreu (2004b) add to this by showing that smaller firms in general are less likely to engage in process innovation, but that entrants have the highest probability of doing so. Coad, Segarra, and Teruel (2016) document heterogeneity in the returns to innovation. Young firms yield larger performance benefits from R&D at the upper quantiles of the productivity distribution, but face larger declines at the lower quantiles.

3 Empirical Framework

In order to study the role of innovation for productivity differences among incumbents and entrants, we employ an augmented Cobb-Douglas production function as econometric framework (Griliches 1979; Hall, Mairesse, and Mohnen 2010):

$$Q_{it} = L_{it}^{\beta l} K_{it}^{\beta k} M_{it}^{\beta m} KI_{it}^{\gamma} KE_{it}^{\delta} e^{u_{it}}. \tag{1}$$

Q_{it}, M_{it}, and K_{it} denote firm i's value of output, material, and physical (tangible) capital in year t and L_{it} refers to its labour input, measured as the number of employees.

In addition to the traditional input factors L_{it}, K_{it} and M_{it}, the production function also accounts for two types of intangible assets, namely the own internal R&D knowledge stock KI_{it} and an external knowledge stock KE_{it}. The external knowledge capital is intended to capture knowledge spillovers among firms. In our empirical analysis, we will differentiate between different types of spillovers: i) intra-industry (horizontal) and inter-industry regional 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; ii) instead of measuring knowledge capital using R&D, we measure intra- and inter-industry regional spillovers using productivity directly and iii) regional spillovers between entrants and incumbents.

u_{it} is an error term for which we assume that it consists of two components: $u_{it} = \omega_{it} + E_{it}$. ω_{it} measures total factor productivity, which is unobserved by the econometrician but observed by the firm and hence affects its input choices.[3] As explained in more detail in section 5, we will make different assumptions on ω_{it} in the empirical analysis, resulting in different estimation methods. In contrast, E_{it} is a productivity shock that is unobserved by both the econometrician and firm at the time the firm decides on its inputs, and thus it is uncorrelated with all input factors.

Taking logs and adopting the convention that lower case letters denote output and inputs in logs, we can write the production function as

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + + \gamma ki_{it} + \delta ke_{it} + \omega_{it} + E_{it} \tag{2}$$

The coefficients β_l, β_k, β_m, γ and δ measure the output elasticities with respect to the corresponding input factors. Our main focus is on estimating γ and δ as they provide a measure for the return to investing in own R&D capital and to external knowledge, respectively.

In our empirical analysis we will allow the production function Equation (2) to differ between entrants and incumbents, either by including a set of interaction terms between $\{k, l, m, ki, ke\}$ and the status of being an entrant or incumbent or by splitting the sample into entrants and incumbents.

4 Data

In order to study the link between innovation and productivity among entrants and incumbents and how they benefit from knowledge spillovers among them, we create a novel data set. We merge two unique data sets that are both conducted at ZEW: the Mannheim Innovation Panel (MIP), which is the German contribution to the European-wide Community Innovation Surveys (CIS), and the IAB/ZEW Mannheim Start-Up panel (MSP), a survey created to study the economic development of newly founded companies in Germany. By combining the two datasets, we obtain representative and comparable firm-level micro data on the innovation behaviour and productivity dynamics of both young and established firms in Germany.

[3]TFP is assumed to be Hicks-neutral. For recent efforts of allowing for labour-augmenting biased technological change, see Doraszelski and Jaumandreu (2018).

The Mannheim Innovation Panel (MIP) is an annual survey, starting in 1993, with the aim to provide representative innovation data for policy and research purposes (for a detailed description see Peters and Rammer 2013). The survey methodology and definitions of innovation indicators follows the recommendations of the OSLO-Manual (OECD, Eurostat 2018), thereby yielding internationally comparable data on innovation activities of German firms. Every second year, it is the German part of the European-wide Community Innovation Surveys (CIS). The target population covers all legally independent firms with their headquarter located in Germany that have five or more employees and that belong to manufacturing, mining, energy and water supply and a large number of service industries. The survey, that is done by mail with an online option, is based on a random stratified sample with industry, size and region serving as stratification criteria. From its beginning, the MIP is designed as a panel, that is the same sample of firms is surveyed every year. But the sample is refreshed every second year to compensate for panel mortality[4] and to account for entering firms. Despite the size threshold of five employees that is lower compared to other international CIS and the refreshment for newly founded firms, MIP data are not well suited for studying the innovation behaviour of entrants. MIP-entrants only cover those newly born firms that passed the threshold of five employees whereas the majority of them remains below this cut-off. Thus, we merge the MIP with the IAB/ZEW Mannheim Start-Up Panel (MSP) that is tailor-made to study entrant behaviour.

The MSP is a joint research project of the German Federal Employment Agency (IAB) and ZEW and since 2008 has encompassed an annual survey of newly established firms in Germany. Participating firms are surveyed continuously during the initial eight years of business activity and covers all economic sectors outside of the primary, public, and energy sectors. Each year, the survey is extended by a stratified random sample of firms founded in the preceding three years. Samples are drawn from the population of economically active businesses in Germany according to private register data from Creditreform, Germany's largest corporate credit rating agency (Bersch, Gottschalk, Müller, and Niefert 2014).[5] Stratification criteria are based on the founding year and industry classifications.[6] Stratification is used in order to oversample high-tech start-ups which are of particular interest to researchers and policy makers. The empirical analyses will control for stratification by including indicator variables for the stratification criteria. The MSP survey is carried out as a computer-assisted telephone interview and gathers information on the firms' founder teams, business profile, innovation activities, as well as economic development. We complement the survey data with additional information on economic performance once they leave the surveyed population after eight years. Additional information on the sampling strategy has been documented by (Fryges, Gottschalk, and Kohn 2010).

In the empirical analysis, entrant status depends on firm age and is not based on the

[4]Firms that ceased business, are not part of the target population any longer, or small and medium-sized firms (up to 499 employees) that did not response in four consecutive survey waves while large firms remain in the sample irrespective of their response behaviour

[5]The Creditreform data also serves as frame population for the MIP.

[6]Until 2013, the MSP was co-organized by KfW, the federal development bank, and funding support from KfW was used as an additional stratification criterion.

sample from which the observation originates. As both survey data sets are based on the same underlying population of all German firms, we can use common identifiers to follow firms across the two surveys. Entrants are therefore 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. We check for duplicate entries and remove the MIP observations for years in which the same entrant firm also participated in the MSP survey. But otherwise we allow a firm to switch from an entrant to an incumbent once it has passed the firm age threshold of eight years.

Most importantly, both data sets allow us to define a set of comparable variables on firm's innovation activities but also on productivity, employment, capital, material and some other control variables needed in order to answer our research questions. We complement the survey data with additional information on the firms' geographic location (zip code and more detailed geo code) and patenting activity. Table 1 gives an overview of the variables used for estimation and their definitions.

We use two different types of labour productivity measures as our main dependent variables and performance outcomes. First, labor productivity is measured as revenue productivity, that is as ratio of sales to the number of employees. In the following, we also simply call this variable productivity. Second, value added per employee is used as an alternative measure of firm-level labour productivity. Value added, intended 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, is defined in both data sets as the difference between sales revenues and intermediate inputs.

As participation to both surveys is voluntary, both panels are unbalanced. We therefore decided not to calculate an R&D stock using the perpetual inventory method but to generally proxy knowledge capital using R&D expenditure. Hence, internal knowledge capital is measured as the R&D expenditure in a given year while external knowledge capital is approximated as the sum of R&D spending by other firms within the same region in a given year. Region is defined by labour market regions in Germany. As reported in Table 1, we differentiate between other firms within the same industry of the focal firm or outside and further split the group of other firms into entrants and incumbents in order to identify knowledge spillovers among and across the group of entrants and incumbents as well. Instead of capturing knowledge spillovers using R&D expenditure, we alternatively use the average productivity of other firms (entrants/incumbents) within the same region inside or outside the industry of the focal firm.

Overall, the estimation panel consists of 65,576 firm-year observations from 25,659 firms. The minimum number of participation per firm is 1, the maximum 14 and the average number is about 2.6 years. 46.6% of all firm-year observations stem from entrant firms. The average age among entrant firms 3.6 years compared to 40.5 years for incumbents.

Summary statistics for all variables are reported for the full sample and separately for entrants and incumbents in Table 2. All quantitative variables (except firm age) are in

Table 1: Variable Definitions

Variable	Unit	Definition
Entrant	1/0	1 for firm-year observations for which the firm is at most eight years old
Incumbent	1/0	1 for firm-year observations for which the firm older than years
Productivity	log	Labor productivity measured as revenue productivity, i.e. 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.Value added is defined as revenue minus material costs.
Capital	log	Stock of tangible assets in year t calculated using the perpetual method, i.e. as sum of depreciated capital stock in $t-1$ plus investments in year t (discount rate 20%) divided by the number of employees
Employees	log	Number of employees in year t (in headcounts)
Material	log	Expenses for material and other intermediate inputs in year t divided by the number of employees
R&D Expenditure	log	Research and development expenses in year t divided by the number of employees
Intraindustry R&D	log	Sum of R&D expenditures by other firms in the same region, three digit NACE code and year
Interindustry R&D	log	Sum of R&D expenditures by other firms in the same region and year with a different three digit NACE code
Intraindustry Productivtiy	log	Mean labor productivity of other firms in the same region, three digit NACE code and year
Interindustry Productivity	log	Mean labor productivity of other firms in the same region and year with a different three digit NACE code
Intraindustry R&D by Entrants	log	Sum of R&D expenditures by other entrant firms in the same region, three digit NACE code and year
Interindustry R&D by Incumbents	log	Sum of R&D expenditures by other incumbent firms (age $>$ eight years) in the same region and year with a different three digit NACE code
Intraindustry Productivtiy of Entrants	log	Mean labor productivity of other entrant firms in the same region, three digit NACE code and year
Interindustry Productivity of Incumbents	log	Mean labor productivity of other incumbent firms (age $>$ eight years) in the same region and year with a different three 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 sector
Firm age	int	Age variable counting years since a firm took up economic activity
MSP	1/0	1 if the observation stems from the Mannheim Start-Up Panel
East	1/0	1 if the firm is located in Eastern Germany

log values since we estimate the log-linear equation (2) of the Cobb-Douglas production function. The summary statistics generally emphasize substantial differences between incumbents and entrants. Incumbent firms have on average significantly higher productivity, larger capital stocks, higher material expenses, more employees, and higher R&D expenditures. The same pattern emerges for the median values. For example, incumbents have a median productivity that is more than twice as large as that of entrants (132,664 compared to 58,333 Euro).

The sample of incumbent firms furthermore includes a significantly larger share of companies that are based in Eastern Germany. Interestingly, the measures for regional average productivity and regional R&D expenditure show that entrants on average are based in regions with significantly more external knowledge capital available and significantly higher average productivity. With the exception of intra-industry average productivity by (other) incumbent firms, these differences hold for both within and across industry comparisons. However, it should be noted that the narrow definition of industry sector membership (based on three digit NACE Rev. 2 codes) has implications for the values reported here. Almost 45% of incumbents in the sample do not have a firm in the same industry within the same labor market region. For entrants, this value is only 30%. As such, the mean values reported in Table 2 effectively depict weighted averages.[7]

[7] The difference in the share of firms with 'peers' in the same region between incumbents and entrants also points to potential differences in location choice between the two groups. We return to this point in the conclusion.

Table 2: Summary Statistics

	Full Sample		Incumbents		Entrants		Difference	
Variable	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Incumbents - Entrants	
Log(Productivity)	11.408	(1.238)	11.888	(1.011)	10.858	(1.246)	1.030	(0.000)***
Log(Value Added Productivity)	10.882	(1.077)	11.243	(0.816)	10.441	(1.186)	0.802	(0.000)***
Log(Capital)	9.702	(1.678)	10.057	(1.853)	9.295	(1.342)	0.761	(0.000)***
Log(Material)	9.984	(1.849)	10.675	(1.709)	9.192	(1.678)	1.482	(0.000)***
Log(Employees)	3.037	(2.315)	4.331	(2.169)	1.553	(1.41)	2.778	(0.000)***
Log(R&D Expend.)	3.169	(4.167)	3.411	(4.135)	2.891	(4.187)	0.520	(0.000)***
Log(Intraindustry R&D)	4.483	(6.530)	3.676	(6.284)	5.408	(6.682)	-1.732	(0.000)***
Log(Interindustry R&D)	17.486	(3.852)	17.210	(3.883)	17.687	(3.806)	-0.377	(0.000)***
Log(Intraindustry R&D by Entrants)	2.705	(5.084)	1.487	(4.010)	4.102	(5.778)	-2.615	(0.000)***
Log(Intraindustry R&D by Incumbents)	3.172	(6.045)	3.066	(5.994)	3.293	(6.100)	-0.227	(0.000)***
Log(Intraindustry Productivity)	5.737	(6.000)	4.812	(6.002)	6.799	(5.819)	-1.987	(0.000)***
Log(Interindustry Productivity)	12.688	(1.300)	12.669	(1.516)	12.709	(0.997)	-0.040	(0.000)***
Log(Intraindustry Prod. by Entrants)	3.221	(5.165)	1.069	(3.407)	5.689	(5.706)	-4.620	(0.000)***
Log(Intraindustry Prod. by Incumbents)	3.113	(5.431)	3.984	(5.813)	2.114	(4.764)	1.870	(0.000)***
Firm Age	23.333	(34.840)	40.509	(40.439)	3.635	(1.987)	36.874	(0.000)***
East	0.258	(0.438)	0.319	(0.466)	0.189	(0.391)	0.130	(0.000)***
MSP	0.406	(0.491)	–	–	0.873	(0.333)	–	–

Notes: The full sample encompasses 65,576 observations of 25,659 firms. The subsample of incumbent firms consists of 35,032 observations of 11,776 firms while the subsample of entrant firms includes 30,544 observations of 14,593 firms. The last two columns show the difference in means between incumbents and entrants as well as p-values and significance levels from a two sample t-test with unequal variances. ***, ** and * indicate significance at the 1%, 5% and 10% level.

5 Results

In the following empirical analysis, we compare the role of investing in own innovation for productivity among entrants and incumbents and also how they benefit from knowledge spillovers in three subsequent steps. First, in subsection 5.1, we estimate the production function in equation (2) focusing on the average rate of return to own R&D investments for the group of entrants and incumbents. As it seems unlikely that most firms, especially among entrants, get the average return to innovation, we provide a more nuanced picture in subsection 5.2 by studying heterogeneous productivity effects of R&D. Using a quantile regression approach, we measure how the impact of innovation on productivity varies along the conditional productivity distribution of entering and established firms, respectively. In a final step, we augment the production function by adding external knowledge capital in subsection 5.3. This allows us to study the differential learning of entrants and incumbents from knowledge that is produced outside its own firm boundaries. We account for different types of external knowledge pools reflecting learning within and between industries for both groups of firms but also within and between the group of entrants and incumbents.

5.1 Average Returns to Own Innovation for Entrants and Incumbents

The first step of analysis is to understand how the productivity effects of innovation differ between entrants and incumbent firms using the empirical framework outlined in section 3. As mentioned there, depending on the assumptions on ω_{it} in equation (2), we can employ different estimation methods. First, we can make the strong assumption that $\omega_{it} = 0$. This implies that there are only idiosyncratic shocks to productivity which are unknown to the firm at the time it makes its input decision. Under this assumption pooled OLS is the best unbiased estimator. However, a violation of this assumptions leads to inconsistent OLS results. Second, to relax this strong assumption we therefore allow for unobserved heterogeneity among firms but assume that the individual unobserved productivity is time-constant. Assuming that $\omega_{it} = \omega_i$ favours the fixed effect (FE) estimator. Finally, we use a more elaborate estimation method to tackle the potential endogeneity bias of OLS by allowing for unobserved productivity shocks ω_{it} that are known to firm when it makes its input choices. In particular, we use the control function-based approaches to estimating production functions laid out by Olley and Pakes (1996) (OP) and Ackerberg, Caves, and Frazer (2015) (ACF). These approaches address the endogeneity bias concerning productivity shocks that are known to the firm but unobservable to researchers by assuming that they can be inverted out from certain firm inputs, if the firm has adjusted these optimally in response to the shock it observed.[8]

Table 3 reports the results of pooled OLS and FE regressions of the Cobb-Douglas production function. The dependent variable labour productivity is measured as revenue

[8]Olley and Pakes (1996) shows that a firm's observable investment decision can be used to back out the unobserved productivity shock, if the investment was chosen optimally in response. Ackerberg, Caves, and Frazer (2015) propose a similar approach using intermediate inputs and relaxing certain functional form assumptions. See also Levinsohn and Petrin (2003) for a comparable modelling strategy.

productivity. In these pooled specifications, we employ the full sample containing both entrant and incumbent firms and interact all input variables with entrant status to differentiate between the productivity effects for both groups of firms. Due to the log-linear specification, the resulting coefficients of the input variables can be interpreted as elasticities.

Looking at the output elasticity of R&D expenditures, the first major finding is that the average return to investing in R&D is significantly positive for both entrants and incumbents. This holds in both OLS and FE estimation. Second, on average entrants benefit more from investing an additional 1 % in R&D than incumbents. For incumbents, the output elasticity of R&D is 3.3 % in OLS which reduces to 1.6 % in the FE regression, when we allow for individual-specific time-constant unobserved productivity. For entrants, the results show a noticeably larger average productivity effect of R&D expenditure, with 5.7 % in OLS and 5.5 % in FE. The difference in the average return to R&D between entrants and incumbents is significant at the 5% level in OLS ($p-value = 0.0167$) and at the 1% level in FE ($p- \ value = 0.0025$). Our 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.

The positive and highly significant coefficient of firm age for newly born firms indicate strong learning effects in terms of productivity improvements with every additional year the firm survives on the market. These learning effects associated with firm age become much smaller and phase out in later stages of firm life.

Besides differences in the productivity effects of innovation, we also find that entrants seem to experience larger productivity gains from additional capital inflow and additional employees. While the respective coefficients for entrants are significantly larger than the ones for incumbents, no statistically significant difference can be observed between the productivity effects of material inputs. Both entrants and incumbents from the eastern states in Germany are significantly less productive than firms from other parts of the country.

Finally, it is interesting to note that the difference between the respective R&D coefficients in the OLS and FE estimations is much smaller for entrants than for incumbents. This indicates that fixed effects are less prevalent and important in the first years after market entry when a firm is still in its learning phase and characterized by a high organizational agility. However, fixed effects matter far more for well-established incumbent firms.

Table 4 displays the additional OP and ACF results. The dependent variable in the OP results in Column (1) and (2) is revenue productivity. Since identification in the Ackerberg, Caves, and Frazer (2015) model is limited to value added production functions, we use value

Table 3: Productivity Effects of Innovation for Entrants and Incumbents in Germany: OLS & FE

	(1) OLS	(2) FE
Log(Capital)×Incumbent	0.071***	0.033***
	(0.004)	(0.004)
Log(Capital)×Entrant	0.128***	0.084***
	(0.006)	(0.010)
Log(Material)×Incumbent	0.414***	0.154***
	(0.006)	(0.008)
Log(Material)×Entrant	0.401***	0.229***
	(0.006)	(0.011)
Log(Employees)×Incumbent	0.012***	-0.260***
	(0.003)	(0.017)
Log(Employees)×Entrant	0.048***	-0.308***
	(0.006)	(0.015)
Log(R&D Exp.)×Incumbent	0.033***	0.016***
	(0.004)	(0.004)
Log(R&D Exp.)×Entrant	0.057***	0.055***
	(0.009)	(0.013)
Firm Age×Incumbent	-0.007	0.031*
	(0.007)	(0.017)
Firm Age×Entrant	0.308***	0.532***
	(0.010)	(0.015)
East×Incumbent	-0.176***	-0.075
	(0.011)	(0.060)
East×Entrant	-0.108***	-0.135*
	(0.017)	(0.073)
MSP	-0.209***	
	(0.022)	
Intercept	6.379***	10.577***
	(0.131)	(0.310)
Industry Dummies	✓	✓
Year Dummies	✓	✓
R-squared	0.663	0.320
Observations	65,576	65,576

Note: Results from ordinary least squares and fixed effects regressions. Robust standard error clustered on the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 4: Productivity Effects of Innovation for Entrants and Incumbents in Germany: OP & ACF

	(1) OP (Incumbents)	(2) OP (Entrants)	(3) ACF (Incumbents)	(4) ACF (Entrants)
Log(R&D Exp.)	0.024***	0.029***	0.057***	0.125***
	(0.004)	(0.010)	(0.002)	(0.002)
Log(Employees)	0.009***	0.043***	0.019***	0.053***
	(0.002)	(0.006)	(0.000)	(0.001)
Log(Material)	0.399***	0.380***		
	(0.006)	(0.006)		
Log(Capital)	0.076***	0.147***	0.127***	0.281***
	(0.026)	(0.029)	(0.000)	(0.001)
East	-0.167***	-0.096***	-0.260***	-0.132***
	(0.001)	(0.009)	(0.000)	(0.001)
MSP	0.005*	-0.273***	0.005***	-0.554***
	(0.003)	(0.011)	(0.000)	(0.001)
Firm Age	-0.009***	0.327***	0.008***	0.365***
	(0.002)	(0.020)	(0.000)	(0.002)
Industry Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Observations	30,677	22,331	30,297	20,722

Note: Results from control function based structural productivity estimators. Bootstrapped standard errors (20 iterations) in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

added productivity as dependent variable in Column (3) and (4) instead. To mitigate the complexity of including additional interaction effects in these structural specifications, we now run split-sample regressions, separately for incumbents and entrants. Column (1) and (3) contain results for incumbents, while Column (2) and (4) report coefficients on entrant firms. As before in Table 3, we see positive and significant returns to investing in R&D for both young and established firms. While the OP coefficient for incumbents falls well between the OLS and FE results, it becomes noticeably lower compared to OLS and FE for entrants. This results in a lower productivity differential of R&D investment between entrants and incumbents using OP. However, the results still suggest that newly entering firms seem to experience larger productivity improvements of innovation than firms that are already established in the market. Given that we use value added productivity instead of revenue productivity as dependent variable for ACF, the magnitude is not directly comparable to OLS, OP and FE. But the ratio of output elasticity of R&D between entrants and incumbents is (2) is in the same ballpark as found in OLS and FE.

To sum up, we find a positive and significant average effect of firm investment into R&D on productivity for both entrants and incumbents. Even after allowing input factors to depend on unobserved productivity shocks, our results still show that the magnitude of the average rate of return to R&D differs considerably between entrant firms that are new to the market and incumbent firms that are mature and established.

5.2 Firm-level Heterogeneity in Returns to Innovation for Entrants and Incumbents

While we have accounted for firm-level heterogeneity, that is for unobserved factors driving both innovation and productivity, in various ways in the last section, we still have assumed and estimated a constant (average) rate of return to innovation for both groups of firms. But prior evidence, though still scarce, has found evidence for heterogeneity in the rate of returns to innovation along the productivity distribution for incumbent firms (see Coad and Rao 2008; Segarra and Teruel 2011; Mata and Woerter 2013; Bartelsman, Dobbelaere, and Peters 2015; Montresor and Vezzani 2015). We expect heterogeneity in the rate of return to innovation to show up among entrants as well and to be even higher than among incumbent firms. Firms entering the market have generally no or only little experience in innovation and are still at the beginning of their learning curve. This implies on the one hand that it is more likely that their innovation projects fail and that they experience no productivity improvements. On the other hand, if the innovation project succeeds, they may disproportionately benefit from investing in R&D.

In order to study the firm-level heterogeneity in the returns to innovation for entrants and incumbents, we use the well established quantile regression approach (Koenker and Bassett 1978). We model the conditional productivity distribution at various quantiles θ $(0 < \theta < 1)$, conditional on the same set of explanatory variables used in section 5.1. More specifically, we estimate pooled simultaneous-quantile regressions for $\theta \in \{0.05, 0.10, 0.20, 0.25, 0.30, 0.40, 0.50, 0.60, 0.70, 0.75, 0.80, 0.90, 0.95\}$ separately for entrants and incumbents. Table 5 shows results for some selected quantiles for both groups of firms. Standard errors are bootstrapped using 20 replications.

The results for the incumbents shows two interesting findings. First, the coefficient of R&D expenditure is significantly positive for all quantiles indicating that all firms benefit from investing in R&D in terms of productivity improvements. But not all firms benefit to the same extent, thus confirming firm-level heterogeneity in the returns to R&D as found in prior literature. While firms in the bottom 10% of the productivity distribution have an output elasticity of 0.014, it is more than twice as large for firms with median productivity (0.032). Interestingly the productivity impact of R&D remains fairly stable for firms at higher quantiles.

A quite different pattern emerges for entrants as not all of them benefit from investing in R&D. The 10% least-performing enterprises experience a significantly negative return to R&D whereas enterprises at the 20^{th} quantile experience neither a significant loss nor gain in productivity. The productivity effects become significantly positive from the 25^{th} percentile onwards. Furthermore, we find steadily increasing marginal returns to own R&D investment as we move from the 25^{th} to the 95^{th} quantile. Compared to firms at the 25^{th} quantile of the productivity distribution who have an estimated output elasticity of about 0.015, firms at the median have a marginal productivity that is about 4,5 times larger and it is even 10 times larger for firms at the 95^{th} percentile.

In a nutshell, these results confirm our hypothesis that firm-level heterogeneity in the returns to innovation is larger for entrant firms. Entering firms at the lower buttom of the productivity distribution fail to benefit from investing in R&D while at higher quantiles of the distribution entrants experience disproportionately high and increasing returns to innovation. Though our results cannot uncover the specific channel, the results are consistent with the view of a learning curve and that learning effects might be particularly high for entrant firms.

Table 5: Heterogenous Productivity Effects of Innovation for Entrants and Incumbents in Germany: Quantile regression results

	Entrants						Incumbents					
	q10	q25	q50	q75	q90	q95	q10	q25	q50	q75	q90	q95
Log(Capital	0.090***	0.098***	0.111***	0.113***	0.122***	0.125***	0.036***	0.047***	0.063***	0.073***	0.092***	0.115***
	(0.008)	(0.005)	(0.004)	(0.005)	(0.009)	(0.010)	(0.003)	(0.001)	(0.002)	(0.002)	(0.004)	(0.008)
Log(Material)	0.638***	0.528***	0.423***	0.361***	0.329***	0.317***	0.604***	0.554***	0.496***	0.450***	0.420***	0.410***
	(0.012)	(0.004)	(0.004)	(0.003)	(0.006)	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Log(Employees)	0.069***	0.057***	0.034***	0.000	-0.016	-0.009	0.011***	0.009***	0.06***	0.006**	0.000	-0.009
	(0.009)	(0.004)	(0.003)	(0.004)	(0.010)	(0.011)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.006)
Log(R&D Exp.)	-0.045***	0.015**	0.055***	0.070***	0.096***	0.124***	0.014***	0.022***	0.032***	0.034***	0.033***	0.026***
	(0.009)	(0.007)	(0.006)	(0.005)	(0.009)	(0.013)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.008)
Firm Age	0.466***	0.307***	0.203***	0.140***	0.099***	0.070***	0.019***	0.006***	0.002	-0.008**	-0.026***	-0.019
	(0.021)	(0.011)	(0.009)	(0.007)	(0.014)	(0.023)	(0.004)	(0.002)	(0.003)	(0.003)	(0.008)	(0.012)
East	-0.071***	-0.081***	-0.107***	-0.168***	-0.217***	-0.2229***	-0.085***	-0.128***	-0.160***	-0.199***	-0.237***	-0.274
	(0.020)	(0.009)	(0.011)	(0.011)	(0.030)	(0.035)	(0.008)	(0.005)	(0.006)	(0.008)	(0.013)	(0.020)
Industry Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R2	0.3426	0.3245	0.2958	0.2801	0.2670	0.2559	0.5543	0.5492	0.5347	0.5056	0.4673	0.4384
Observations	31230						35587					

Notes: Results are based on pooled simultaneous-quantile regressions for $\theta \in \{0.05; 0.10; 0.20; 0.25; 0.30; 0.40; 0.50; 0.60; 0.70; 0.75; 0.80; 0.90; 0.95\}$. Results for other quantiles are available upon request. Bootstrapped standard errors (20 replications). ***, ** and * indicate significance at the 1%, 5% and 10% level. Regions Dummy variable for firms

5.3 Spillover Effects

A key question related to the productivity effects of innovation is the degree to which a firm's innovation may also be able to impact another firm's performance. These spillover effects are very 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, resulting in a sup-optimal low level of R&D from a social point of view. Besides using the stock of knowledge the firm internally creates by investing in R&D, the firm may also be able to learn from external knowledge developed and held by other firms that it is interacting with. Simple examples of such processes include firms learning from collaboration partners with whom they share a supply chain with or learning from competitors who provide a visible performance benchmark in market competition. In this section, we examine the productivity benefits that entrant and incumbent firms gain from geographic proximity to external knowledge stocks 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 5.3.1 measures spillovers using the sum of R&D expenditures of other firms, subsection 5.3.2 measures knowledge spillovers using the average productivity of other firms. Subsection 5.3.3 further differentiates other firms into entrants and incumbents.

5.3.1 Inter- and intraindustrial R&D spillovers

External knowledge capital is intended to capture the knowledge that firms may have access to beyond the knowledge they themselves produce through investment in R&D. 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. For each firm, we define external knowledge capital as the accumulation of knowledge that is generated by other firms that are geographically close to the focal firm. Geographically close firms are those within the same labour market region. 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 (defined by three digit NACE codes). That is, for each firm we compute the leave-one-out sum of R&D expenditure per year and industry in the labor market region where it operates and extend the production function by adding these measures into equation 2.

Table 6 reports the estimates of pooled OLS using these measures of external knowledge capital in a Cobb-Douglas productivity function. For reference, Column (1) includes the OLS results familiar from Table 3 while Column (2)-(4) depict the respective results upon inclusion of intra-industry external knowledge capital, inter-industry external knowledge capital, as well as the combination of the two. Using OLS, we find positive and significant effects of external knowledge for both entrants and incumbents. The effect is, perhaps not

Table 6: Productivity spillovers from nearby R+D expenditure within and across industries, OLS estimates

	(1) Own Innovation	(2) Intraindustrial Spillovers	(3) Interindustrial Spillovers	(4) Intra- and Interindustrial Spillovers
Log(Capital) × Incumbent	0.071***	0.071***	0.071***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(Capital) × Entrant	0.128***	0.129***	0.129***	0.130***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Material) × Incumbent	0.414***	0.413***	0.412***	0.412***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Material) × Entrant	0.401***	0.401***	0.400***	0.401***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Employees) × Incumbent	0.012***	0.011***	0.011***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Log(Employees) × Entrant	0.048***	0.046***	0.046***	0.046***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(R&D Exp.) × Incumbent	0.033***	0.032***	0.031***	0.031***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(R&D Exp.) × Entrant	0.057***	0.053***	0.055***	0.053***
	(0.009)	(0.009)	(0.009)	(0.009)
Firm Age × Incumbent	-0.007	-0.007	-0.005	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)
Firm Age × Entrant	0.308***	0.308***	0.309***	0.308***
	(0.010)	(0.010)	(0.010)	(0.010)
East × Incumbent	-0.176***	-0.176***	-0.167***	-0.168***
	(0.011)	(0.011)	(0.011)	(0.011)
East × Entrant	-0.108***	-0.112***	-0.101***	-0.107***
	(0.017)	(0.017)	(0.017)	(0.017)
MSP	-0.209***	-0.210***	-0.209***	-0.210***
	(0.022)	(0.022)	(0.022)	(0.022)
Log(Intraindustry R&D) × Incumbent		0.004***		0.002***
		(0.001)		(0.001)
Log(Intraindustry R&D) × Entrant		0.007***		0.006***
		(0.001)		(0.001)
Log(Interindustry R&D) × Incumbent			0.008***	0.008***
			(0.001)	(0.001)
Log(Interindustry R&D) × Entrant			0.009***	0.005***
			(0.002)	(0.002)
Intercept	6.379***	6.407***	6.284***	6.309***
	(0.131)	(0.131)	(0.133)	(0.132)
Industry Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
R-squared	0.663	0.664	0.664	0.664
Observations	65,576	65,576	65,576	65,576

Note: R+D expenditure by labour market region and NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

surprisingly, smaller than the productivity effect of firms' own R&D expenditure at about one fourth to one sixteenth the magnitude.

The regression results furthermore show some intriguing contrasts between the productivity effects of young firms and those of established firms. On the one hand, the productivity effect of learning from external knowledge capital within the own industry is larger for entrant firms than it is for incumbents. The estimated elasticity for incumbents lies between 0.2 and 0.4 %, while the estimate for entrants lies between 0.6 and 0.7 %. The difference between the two coefficients is statistically significant, implying that entrants seem to indeed experience higher productivity gains from learning externally within the same industry. On the other hand, the results indicate that incumbent firms have better learning rates from inter-industry knowledge. However, in this case the difference between the two coefficients is statistically not different from zero and excluding within-industry external knowledge capital as in Column (3) of Table 6 even overturns the result order.

The results of estimating the same specifications using FE regressions are generally inconclusive as shown in Table 13. After within-transforming the data there are no significant effects of external knowledge capital on firms' economic performance measured by productivity. In fact, all relevant coefficients merely show minimal levels of oscillation around zero. A tentative interpretation of this finding might be that the presence of productivity spillovers from external knowledge capital is more tied to the level of external knowledge available than the change over time. Assuming that the longer-term presence of external knowledge capital is deciding for spillover effects, or that there is merely little variance in the level of external knowledge available, it would not be a surprise to see these effects removed in fixed effects estimation.

Using the OP and ACF methodology yields spillover effects of external knowledge that are closer to the OLS results than to the ones obtained with FE. Table 8 shows the results of running the respective models separately on the sample of entrants and incumbents. Both approaches reinforce prior OLS results showing that incumbents seem to benefit more from productivity spillovers related to the external knowledge stock held by firms from different industry sectors than from firms that operate within the same three digit NACE code. This result suggests that established and mature firms are on average better at incorporating diverse knowledge that stems from sources outside a firm's usual field of operations. As in the OLS specifications, the OP approach shows that entrants benefit more from within-industry knowledge spillovers than from external knowledge held by firms from other industries. The results using the ACF methodology show a slightly different picture for entrants. While the coefficients for inter- and intra-industrial external knowledge capital show positive point estimates, they are not statistically distinct from zero. In this value added specification, we can therefore not confirm that entrants significantly benefit from R&D spillovers.

Table 7: Productivity spillovers from nearby R+D expenditure within and across industries, Fixed Effects estimates

	(1) Own Innovation	(2) Intraindustrial Spillovers	(3) Interindustrial Spillovers	(4) Intra- and Interindustrial Spillovers
Log(Capital)×Incumbent	0.033***	0.033***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(Capital)×Entrant	0.084***	0.083***	0.083***	0.083***
	(0.010)	(0.010)	(0.010)	(0.010)
Log(Material)×Incumbent	0.154***	0.154***	0.154***	0.154***
	(0.008)	(0.008)	(0.008)	(0.008)
Log(Material)×Entrant	0.229***	0.229***	0.229***	0.229***
	(0.011)	(0.011)	(0.011)	(0.011)
Log(Employees)×Incumbent	-0.260***	-0.260***	-0.260***	-0.260***
	(0.017)	(0.017)	(0.017)	(0.017)
Log(Employees)×Entrant	-0.308***	-0.308***	-0.308***	-0.308***
	(0.015)	(0.015)	(0.015)	(0.015)
Log(R&D Exp.)×Incumbent	0.016***	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(R&D Exp.)×Entrant	0.055***	0.056***	0.055***	0.056***
	(0.013)	(0.013)	(0.013)	(0.013)
Firm Age×Incumbent	0.031*	0.031*	0.031*	0.031*
	(0.017)	(0.017)	(0.017)	(0.017)
Firm Age×Entrant	0.532***	0.532***	0.532***	0.532***
	(0.015)	(0.015)	(0.015)	(0.015)
East×Incumbent	-0.075	-0.075	-0.074	-0.074
	(0.060)	(0.060)	(0.060)	(0.060)
East×Entrant	-0.135*	-0.136*	-0.136*	-0.137*
	(0.073)	(0.073)	(0.073)	(0.073)
Log(Intraindustry R+D)×Incumbent		0.000		0.000
		(0.001)		(0.001)
Log(Intraindustry R+D)×Entrant		-0.001		-0.001
		(0.001)		(0.001)
Log(Interindustry R+D)×Incumbent			0.001	0.001
			(0.001)	(0.001)
Log(Interindustry R+D)×Entrant			-0.000	-0.000
			(0.003)	(0.003)
Intercept	10.577***	10.578***	10.558***	10.560***
	(0.310)	(0.310)	(0.312)	(0.312)
Industry Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
R-squared	0.320	0.320	0.320	0.320
Observations	65,576	65,576	65,576	65,576

Note: Results from fixed effects (within) regressions. Robust standard errors clustered on the firm level. R+D expenditure by labour market region and NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 8: Productivity spillovers from nearby R+D expenditure within and across industries, OP & ACF estimates

	(1) OP (Incumbents)	(2) OP (Entrants)	(3) ACF (Incumbents)	(4) ACF (Entrants)
Log(Employees)	0.006	0.042***	0.019***	0.016***
	(0.004)	(0.005)	(0.002)	(0.004)
Log(Capital)	0.021	0.148***	0.133***	0.255***
	(0.026)	(0.007)	(0.002)	(0.003)
Log(R&D Exp.)	0.022***	0.026***	0.050***	0.120***
	(0.002)	(0.009)	(0.002)	(0.003)
Log(Intraindustry R&D)	0.002***	0.004***	0.013***	0.002
	(0.001)	(0.001)	(0.004)	(0.004)
Log(Interindustry R&D)	0.008***	0.006***	0.023***	0.002
	(0.001)	(0.002)	(0.001)	(0.004)
Firm Age	-0.006	0.327***	0.016***	0.333***
	(0.004)	(0.005)	(0.000)	(0.003)
East	-0.148***	-0.094***	-0.240***	-0.156***
	(0.004)	(0.009)	(0.001)	(0.004)
MSP	0.012***	-0.272***	0.010***	-0.584***
	(0.004)	(0.004)	(0.001)	(0.002)
Industry Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Observations	30,677	22,331	30,297	20,722

Note: Results from control function based structural productivity estimators. Bootstrapped standard errors (20 iterations) in parentheses. R+D expenditure by labour market region and NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

5.3.2 Inter- and intra-industrial productivity spillovers

Firms not only learn from the external knowledge stock that other firms may have generated via R&D investments, they may also learn through observing productivity directly. A firm that operates in a region or market where other market participants display high levels of productivity will have opportunities to learn from these. Such productivity spillovers can take the form of measuring oneself to a competitive benchmark, understanding supply and production networks, or adopting best practices.

To assess the effect that spillovers from other firms' productivity 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 mean of labor productivity in each year per labor market region and three digit NACE industry. These measures are then subsequently included in similar regression specifications as used for the analysis of R&D spillovers in Chapter 5.3.1.

Table 9 displays the results from estimating the respective equations with pooled OLS. A similar pattern as for R&D spillovers emerges. Results indicate that entrants in particular benefit from geographical proximity to high performing firms from within their own industry sector. The output elasticity with respect to intra-industry productivity spillovers amounts to 0.9 %, relative to 0.4 % for incumbent firms. The coefficients are significantly different from zero for both entrants and incumbents. Looking at spillover effects from average productivity of geographically close firms from other industries, a slightly different picture prevails. While still achieving an elasticity of 1.0 percent, the coefficient is only significant at the five %. Moreover, this specific coefficient diminishes in magnitude when we also introduce intra-industry productivity measures into the equation while all other productivity spillover coefficients remain unchanged.

FE results also reveal a pattern that closely follows the results obtained for R&D spillovers. As in Table 7, the most spillover effects disappear following the within-transformation. As before, this may be evidence of the level, rather than the rate of change, of average productivity being the driver behind the spillover effects found in the OLS specifications.

The results for spillover effects from average regional productivity using the OP and ACF approach are shown in Table 11. They corroborate positive and significant spillover effects. In particular incumbents benefit from spillovers across industries on at least the same level than from spillovers within an industry. Conversely, entrants show a higher productivity elasticity for spillover effects within three digit industries rather than across. In the OP specification, the productivity spillover effects are generally larger for entrants than for incumbent firms. That said, positive and significant spillover effects from regional average productivity can be found for both types of firms within and across industries. In the value added specifications used in the ACF model, incumbents actually display larger gains from productivity spillovers than entrants.

5.3.3 Spillovers between entrants and incumbents

So far, we have compared the returns to own innovation of entrants and incumbents and studied spillover effects capturing additional productivity growth for entrants and incumbents based on external knowledge that is generated outside the firm's boundary. But we have not yet paid much attention to the sources behind these spillover effects. In particular, we have considered the entirety of external knowledge available to firms as a single resource. But for example entrants might find it much easier to learn from other entrants than from established firms as they are more comparable in terms of firm size, production technology or organizational structure. As final piece of evidence, we will therefore differentiate between external knowledge that is generated by (other) entrants and external knowledge that is generated by (other) incumbent firms. To assess whether these have differential impact, we generate a number of variables that measure potential spillover sources dependent on whether they originate from entrants or incumbents. Per firm-year observation, we calculate the amount of R&D investment spent by both young and established firms within the same labor market region, year and three digit NACE industry (excluding the firm's own contribution). Similarly, we calculate the average labor productivity of young and established firms in a region-year-industry cell. Understanding these dynamics is interesting for a number of reasons. First, it allows us to better understand the impact that innovative activity and productivity of entrants has on the productivity of firms already in the market. Second, it allows us to examine how innovation and productivity of incumbent

Table 9: Productivity spillovers from nearby mean productivity within and across industries, OLS estimates

	(1) Own Innovation	(2) Intrahorizontal Spillovers	(3) Interhorizontal Spillovers	(4) Intra- and Interhorizontal Spillovers
Log(Capital)× Incumbent	0.071***	0.071***	0.071***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(Capital)× Entrant	0.128***	0.129***	0.128***	0.129***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Material)× Incumbent	0.414***	0.412***	0.413***	0.412***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Material)× Entrant	0.401***	0.401***	0.401***	0.401***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Employees)× Incumbent	0.012***	0.011***	0.012***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Log(Employees)× Entrant	0.048***	0.047***	0.048***	0.047***
	(0.006)	(0.006)	(0.006)	(0.006)
Log(R&D Exp.)× Incumbent	0.033***	0.033***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(R&D Exp.)× Entrant	0.057***	0.054***	0.056***	0.054***
	(0.009)	(0.009)	(0.009)	(0.009)
Firm Age× Incumbent	-0.007	-0.007	-0.006	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)
Firm Age× Entrant	0.308***	0.308***	0.308***	0.308***
	(0.010)	(0.010)	(0.010)	(0.010)
East×Incumbent	-0.176***	-0.178***	-0.175***	-0.177***
	(0.011)	(0.011)	(0.011)	(0.011)
East×Entrant	-0.108***	-0.114***	-0.107***	-0.113***
	(0.017)	(0.017)	(0.017)	(0.017)
MSP	-0.209***	-0.214***	-0.209***	-0.214***
	(0.022)	(0.022)	(0.022)	(0.022)
Log(Intraind. Prod.)× Incumbent		0.004***		0.004***
		(0.001)		(0.001)
Log(Intraind. Prod.)× Entrant		0.009***		0.009***
		(0.001)		(0.001)
Log(Interind. Prod.)×Incumbent			0.008***	0.008***
			(0.002)	(0.002)
Log(Interind. Prod.)×Entrant			0.014***	0.010**
			(0.005)	(0.005)
Intercept	6.379***	6.413***	6.282***	6.324***
	(0.131)	(0.131)	(0.133)	(0.133)
Industry Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
R-squared	0.663	0.664	0.663	0.664
Observations	65,576	65,576	65,576	65,576

Note: Results from ordinary least squares regressions. Robust standard errors clustered on the firm level. Mean labour productivity by labour market region and NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 10: Productivity spillovers from nearby mean productivity within and across industries, Fixed Effects estimates

	(1) Own Innovation	(2) Intrahorizontal Spillovers	(3) Interhorizontal Spillovers	(4) Intra- and Interhorizontal Spillovers
Log(Capital)×Incumbent	0.033***	0.033***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(Capital)×Entrant	0.084***	0.083***	0.084***	0.083***
	(0.010)	(0.010)	(0.010)	(0.010)
Log(Material)×Incumbent	0.154***	0.154***	0.154***	0.154***
	(0.008)	(0.008)	(0.008)	(0.008)
Log(Material)×Entrant	0.229***	0.229***	0.229***	0.229***
	(0.011)	(0.011)	(0.011)	(0.011)
Log(Employees)×Incumbent	-0.260***	-0.260***	-0.260***	-0.260***
	(0.017)	(0.017)	(0.017)	(0.017)
Log(Employees)×Entrant	-0.308***	-0.308***	-0.308***	-0.308***
	(0.015)	(0.015)	(0.015)	(0.015)
Log(R&D Exp.)×Incumbent	0.016***	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Log(R&D Exp.)×Entrant	0.055***	0.055***	0.055***	0.056***
	(0.013)	(0.013)	(0.013)	(0.013)
Firm Age×Incumbent	0.031*	0.031*	0.031*	0.031*
	(0.017)	(0.017)	(0.017)	(0.017)
Firm Age×Entrant	0.532***	0.532***	0.532***	0.532***
	(0.015)	(0.015)	(0.015)	(0.015)
East×Incumbent	-0.075	-0.075	-0.075	-0.075
	(0.060)	(0.060)	(0.060)	(0.060)
East×Entrant	-0.135*	-0.135*	-0.136*	-0.135*
	(0.073)	(0.073)	(0.073)	(0.073)
Log(Intraind. Prod.)×Incumbent		0.000		0.000
		(0.000)		(0.000)
Log(Intraind. Prod.)×Entrant		-0.001		-0.001
		(0.001)		(0.001)
Log(Interind. Prod.)×Incumbent			-0.002*	-0.002*
			(0.001)	(0.001)
Log(Interind. Prod.)×Entrant			-0.002	-0.002
			(0.004)	(0.004)
Intercept	10.577***	10.577***	10.602***	10.602***
	(0.310)	(0.311)	(0.311)	(0.311)
Industry Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
R-squared	0.320	0.320	0.320	0.320
Observations	65,576	65,576	65,576	65,576

Note: Results from fixed effects (within) regressions. Robust standard errors clustered on the firm level. Mean labour productivity by labour market region and NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 11: Productivity spillovers from nearby mean productivity within and across industries, OP/ACF

	(1) OP (Incumbents)	(2) OP (Entrants)	(3) ACF (Incumbents)	(4) ACF (Entrants)
Log(Employees)	0.014**	0.029***	0.024***	0.020***
	(0.005)	(0.006)	(0.003)	(0.001)
Log(Capital)	0.035***	0.128***	0.183***	0.248***
	(0.008)	(0.038)	(0.004)	(0.001)
Log(R&D Exp.)	0.008***	0.024**	0.041***	0.117***
	(0.002)	(0.010)	(0.002)	(0.002)
Firm Age	0.010	0.327***	0.033***	0.343***
	(0.009)	(0.042)	(0.002)	(0.002)
East	-0.183***	-0.149***	-0.297***	-0.197***
	(0.009)	(0.012)	(0.003)	(0.002)
MSP	0.007	-0.257***	0.009*	-0.545***
	(0.008)	(0.042)	(0.005)	(0.003)
Log(Intraind. Prod.)	0.009***	0.017***	0.021***	0.011***
	(0.001)	(0.001)	(0.005)	(0.003)
Log(Interind. Prod.)	0.009***	0.012**	0.023***	0.006***
	(0.002)	(0.006)	(0.007)	(0.002)
Industry Dummies				
Year Dummies	✓	✓	✓	✓
Observations	30,677	22,331	30,297	20,722

Note: Results from control function based structural productivity estimators. Bootstrapped standard errors in parentheses. Mean labour productivity by labour market region and NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

firms correlates with the productivity of other incumbents and whether the other firms' activities also impact the productivity performance of their similarly established competitors. Third, it allows us to study to what extent entrants can learn from firms already in the market. As young firms do need to understand and learn about their competitive environment, it is of key interest whether they can benefit from spillover effects that result from the knowledge and productivity potential held by their incumbent competitors.

Table 12 displays the results from including spillover effects differentiated by the type of firm they originate from in a pooled OLS model. Column (1) includes R&D spillovers from the within industry external knowledge stock available to firms, Column (2) includes measures of average productivity for other firms in the same region and industry, while Column (3) includes both. While the resulting coefficients are all positive and significant in the first two specifications, the results show a greater deal of nuance when looking at the joint specification in Column (3). In particular, we see that spillover effects seem to mainly stem from average productivity of other firms in the same region and industry and that R&D spillovers seem to correlate significantly only with the productivity of incumbent firms. We find evidence for significantly positive productivity spillovers from incumbents to entrants and from incumbents to other incumbents. We also find positive and significant productivity spillovers from entrants to other entrants but not from entrants to incumbents. As such, these results suggest that entrants can learn from observing both the productivity of other entrants and of incumbents, while incumbents mainly learn form the productivity of other incumbents. Surprisingly, we find the opposite pattern for R&D spillovers. We only find positive but small productivity effects from other firms R&D for incumbents learning from entrants. In the OLS specification, we do not find significant spillover effects of R&D expenditures on entrants. These findings contrast some of the results obtained in Chapter 5.3.1 and may point to productivity rather than innovation being the main source behind spillover benefits for newly established firms.

Looking at the FE results, depicted in Table 13, we see a similar picture as in the previous chapters' investigations into spillover effects of external knowledge stocks and average productivity, respectively. Once we apply the within transformation to our data panel, we largely find insignificant effects for both R&D and productivity spillovers. This holds true irrespective of whether the potential spillover source stems from entrant or incumbent firms. In fact, the only borderline significant result seems to point to negative spillover effects from incumbents R&D expenditure for the productivity of entrants. While this coefficient is only significant on the ten percent level, it could point to changes in incumbents' innovation activities partially crowding out productivity contributions by newly established firms. In general, the FE results in Table 13 suggest that if there are regional spillovers of innovation and productivity on other firms' productivity, these may be related to the level of innovative activity and mean productivity rather than changes to them.

Finally, Table 14 reports the OP and ACF results. They are similar to the OLS results. In particular, they point to spillovers from other firms' productivity level playing a larger role than spillovers from access to other firm's knowledge stock. While the average productivity of other entrants and incumbents within a firm's region and industry correlated positively with the productivity of both entrants and incumbents, the correlation between productivity and the available external knowledge stock is not significant in the OP specifications. We do however find a positive and significant effect of external knowledge on the productivity of incumbents in the value added specification of the ACF model. R&D expenditure by both entrants and incumbents within the same industry and region is positively associated with productivity of incumbent firms. Entrants, on the contrary, seem to only benefit from productivity spillovers stemming from other entrants. The OP results do however not indicate significant correlation between entrants' R&D activity and incumbent productivity or vice versa.

Table 12: Spillovers between entrants and incumbents, OLS estimates

	(1) R+D Spillovers	(2) Productivity Spillovers	(3) R+D and Productivity Spillovers
Log(Capital)×Incumbent	0.071***	0.071***	0.071***
	(0.004)	(0.004)	(0.004)
Log(Capital)×Entrant	0.129***	0.130***	0.130***
	(0.006)	(0.006)	(0.006)
Log(Material)×Incumbent	0.413***	0.412***	0.412***
	(0.006)	(0.006)	(0.006)
Log(Material)×Entrant	0.401***	0.401***	0.401***
	(0.006)	(0.006)	(0.006)
Log(Employees)×Incumbent	0.011***	0.011***	0.010***
	(0.003)	(0.003)	(0.003)
Log(Employees)×Entrant	0.046***	0.047***	0.046***
	(0.006)	(0.006)	(0.006)
Log(R&D Exp.)×Incumbent	0.032***	0.033***	0.032***
	(0.004)	(0.004)	(0.004)
Log(R&D Exp.)×Entrant	0.053***	0.053***	0.053***
	(0.009)	(0.009)	(0.009)
Log(Intraind. prod. by Entrants)×Incumbent		0.003**	0.002
		(0.001)	(0.001)
Log(Intraind. prod. by Entrants)×Entrant		0.008***	0.006***
		(0.001)	(0.001)
Log(Intraind. prod. by Incumbents)×Incumbent		0.004***	0.002**
		(0.001)	(0.001)
Log(Intraind. prod. by Incumbents)×Entrant		0.006***	0.004**
		(0.001)	(0.002)
Log(Intraind. R&D by Entrants)×Incumbent	0.003***		0.002**
	(0.001)		(0.001)
Log(Intraind. R&D by Entrants)×Entrant	0.006***		0.002
	(0.001)		(0.002)
Log(Intraind. R&D by Incumbents)×Incumbents	0.003***		0.002
	(0.001)		(0.001)
Log(Intraind. R&D by Incumbents)×Entrant	0.004***		0.002
	(0.001)		(0.001)
Firm Age×Incumbent	-0.007	-0.007	-0.007
	(0.007)	(0.007)	(0.007)
Firm Age×Entrant	0.308***	0.308***	0.308***
	(0.010)	(0.010)	(0.010)
East×Incumbent	-0.178***	-0.180***	-0.180***
	(0.011)	(0.011)	(0.011)
East×Entrant	-0.114***	-0.120***	-0.119***
	(0.017)	(0.017)	(0.017)
MSP	-0.211***	-0.218***	-0.217***
	(0.022)	(0.022)	(0.022)
Intercept	6.412***	6.418***	6.425***
	(0.131)	(0.131)	(0.131)
Industry Dummies	✓	✓	✓
Year Dummies	✓	✓	✓
R-squared	0.664	0.664	0.664
Observations	65,576	65,576	65,576

Notes: Results from ordinary least squares regressions. Robust standard errors clustered on the firm level. R+D expenditure and average productivity by labour market region and firm age within NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 13: Spillovers between entrants and incumbents, Fixed Effect estimates

	(1) R+D Spillovers	(2) Productivity Spillovers	(3) R+D and Productivity Spillovers
Log(Capital)×Incumbent	0.033***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)
Log(Capital)×Entrant	0.084***	0.083***	0.084***
	(0.010)	(0.010)	(0.010)
Log(Material)×Incumbent	0.154***	0.154***	0.154***
	(0.008)	(0.008)	(0.008)
Log(Material)×Entrant	0.229***	0.229***	0.229***
	(0.011)	(0.011)	(0.011)
Log(Employees)×Incumbent	-0.260***	-0.260***	-0.260***
	(0.017)	(0.017)	(0.017)
Log(Employees)×Entrant	-0.308***	-0.308***	-0.308***
	(0.015)	(0.015)	(0.015)
Log(R&D Exp.)×Incumbent	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)
Log(R&D Exp.)×Entrant	0.056***	0.055***	0.056***
	(0.013)	(0.013)	(0.013)
Log(Intraind. prod. by Entrants)×Incumbent		0.000	0.000
		(0.001)	(0.001)
Log(Intraind. prod. by Entrants)×Entrant		-0.001	-0.001
		(0.002)	(0.002)
Log(Intraind. prod. by Incumbents)×Incumbent		0.000	0.000
		(0.001)	(0.001)
Log(Intraind. prod. by Incumbents)×Entrant		0.001	0.002
		(0.002)	(0.002)
Log(Intraind. R&D by Entrants)×Incumbent	-0.000		-0.000
	(0.001)		(0.001)
Log(Intraind. R&D by Entrants)×Entrant	-0.000		-0.000
	(0.002)		(0.002)
Log(Intraind. R&D by Incumbents)×Incumbents	-0.000		-0.000
	(0.001)		(0.001)
Log(Intraind. R&D by Incumbents)×Entrant	-0.002		-0.002*
	(0.001)		(0.001)
Firm Age×Incumbent	0.031*	0.031*	0.031*
	(0.017)	(0.017)	(0.017)
Firm Age×Entrant	0.533***	0.532***	0.533***
	(0.015)	(0.015)	(0.015)
East×Incumbent	-0.075	-0.075	-0.075
	(0.060)	(0.060)	(0.060)
East×Entrant	-0.136*	-0.135*	-0.136*
	(0.073)	(0.073)	(0.073)
Intercept	10.580***	10.577***	10.581***
	(0.312)	(0.310)	(0.312)
Industry Dummies	✓	✓	✓
Year Dummies	✓	✓	✓
R-squared	0.320	0.320	0.320
Observations	65,576	65,576	65,576

Note: Results from fixed effects (within) regressions. Robust standard errors clustered on the firm level. R+D expenditure and average productivity by labour market region and firm age within NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 14: Spillovers between entrants and incumbents, OP/ACF estimates

	(1) OP (Incumbents)	(2) OP (Entrants)	(3) ACF (Incumbents)	(4) ACF (Entrants)
Log(Employees)	0.014***	0.031***	0.024***	0.016***
	(0.005)	(0.006)	(0.001)	(0.005)
Log(Capital)	0.047***	0.130***	0.184***	0.255***
	(0.006)	(0.034)	(0.001)	(0.003)
Log(R&D Exp.)	0.007***	0.022**	0.038***	0.113***
	(0.002)	(0.010)	(0.002)	(0.003)
Firm Age	0.001	0.325***	0.034***	0.338***
	(0.011)	(0.041)	(0.002)	(0.005)
East	-0.183***	-0.153***	-0.305***	-0.216***
	(0.008)	(0.018)	(0.001)	(0.005)
MSP	0.018**	-0.269***	0.009***	-0.559***
	(0.008)	(0.013)	(0.002)	(0.004)
Log(Intraind. Prod. by Entrants)	0.009***	0.014***	0.019***	0.007**
	(0.001)	(0.002)	(0.003)	(0.003)
Log(Intraind. Prod. by Incumbents)	0.007***	0.007***	0.018***	0.007
	(0.001)	(0.002)	(0.001)	(0.004)
Log(Intraind. R&D by Entrants)	0.000	0.003	0.011***	0.007
	(0.001)	(0.002)	(0.001)	(0.005)
Log(Intraind. R&D by Incumbents)	0.001	-0.001	0.014***	0.001
	(0.001)	(0.001)	(0.002)	(0.006)
Industry Dummies				
Year Dummies	✓	✓	✓	✓
Observations	30,677	22,331	30,297	20,722

Note: Results from control function based structural productivity estimators. Bootstrapped standard errors in parentheses. R+D expenditure and average productivity by labour market region and firm age within NACE3-level industry codes. ***, ** and * indicate significance at the 1%, 5% and 10% level.

6 Conclusions, Limitations und Future Research

Productivity is a key driver of economic growth and performance. This paper studies and compares the role innovation plays for driving productivity for two important groups of firms in the economy: entrants and incumbents. In particular, we investigate how average returns to innovation differ between entrants and incumbents, to what degree these returns are heterogeneous and how much they can learn and benefit from knowledge produced outside the firm boundaries by other entering or incumbent firms.

By pooling two existing survey-based micro data sets, the Mannheim Innovation Panel (MIP) and the IAB/ZEW Start-Up Panel (MSP), we create a novel and representative firm data panel data set including comparable information on young and established firm's R&D activities and input and output measures necessary to study productivity. By using available information on firms' geographic location and industry sector we construct a number of proxies for regional productivity and innovation spillovers.

Our analysis shows six major findings. First, we find a robust positive and significant effect of investing in R&D on firm-level productivity. This finding holds true for both entrant and incumbent firms. Second, the average return to innovation for entrants significantly exceeds the return for incumbents. Third, while we find that entrants tend to have larger returns to innovation on average, we also find that they experience considerably more heterogeneity with regards to those returns. Using quantile regressions, we show that productivity gains from innovation for incumbents vary within a relatively narrow range of 1.4 to 3.4 %. We find the returns to innovation for entrants to fall into a much wider bandwidth from -4.5 to 12.4%, with low-productive firms even experiencing negative returns.

Fourth, both entrants and incumbents benefit from knowledge that is generated by other firms in the same labour region in Germany. We find these spillover effects to hold both within and across industry sectors. Fifth, while positive and significant for both, entrants on average benefit more from spillovers within industrial sectors while incumbents benefit more from the activities from firms in different industries. Besides innovation spillovers, we also find evidence for regional spillovers from the aggregate productivity level of other firms. Both entrants and incumbents situated in regions with higher average productivity of other firms tend to display higher productivity themselves. Specifications using measures of both innovation and productivity spillovers suggest that the spillover effects from regional productivity actually outpace the benefits of external knowledge capital generated through other firms' innovation activities. Sixth, finally, in examining whether these spillovers themselves stem from entrants or incumbents, we show that the productivity of entrants in particular is positively affected by learning from other productive entrants. We also find evidence of positive spillovers from entrants' R&D investment on incumbents' productivity in the same region and industry.

Our analysis is still subject to a number of limitations and caveats that are on the agenda for future research. First, we do not account for endogenous location choice. Our results clearly indicate that there is correlation between entrant firms' productivity and the average productivity of other firms situated in the same labor market region. Location, however, is not random but a choice variable at the discretion of the entrepreneur. It is therefore conceivable that positive correlation between firms' productivity is partly determined by high productivity entrants establishing themselves geographically close to already productive incumbents. While such dynamics do not reduce the importance of our findings, future extensions of this work may want to model location choice endogenously. Second, yet we do not explicitly account for differences in the likelihood of exit between different types of firms. Entrants and incumbents are likely to differ in their probability of remaining in the market and this difference is likely connected to productivity. In fact, positive correlation between productivity and survival is consistent finding in existing literature (Syverson 2011). While prior research using MIP data has pointed to sample attrition not being determined by productivity but the voluntary participation nature of the underlying survey, selection bias is likely to affect participation in the MSP start-up survey. Given that exit information can be retrieved from the underlying firm population, future extensions of this work will account for differential survival probabilities. Third, we consider innovation and productivity spillovers in general and do not differentiate with regards to the degree in which different industries are more or less distant from another in technology space. Certain industries may be more likely to generate innovation and productivity spillovers than others. Moreover, the spillover potential between industries may differ depending on firms in different industries produce complementary or substitute goods. Fourth, we study the effect of innovation on productivity by focusing on expenditures for R&D as a proxy of firms' knowledge stock. Yet, we do not give emphasis to firm-level nuances in innovation behaviour and aptitude. Besides the raw amount of expenditure on R&D, future research may also want to consider whether firms engage in innovation at all and whether, for instance, firms' receptiveness for spillover effects may be a function of own R&D choices or other firm characteristics.

Despite its caveats, our analysis provides a number of implications for firms and policy makers. First, compared to incumbents we find the returns to R&D for entrants are higher on average but also more volatile. We document considerable heterogeneity in the productivity effect of innovation for entrants, indicating that in some cases innovation may be costly for young firms. Second, we find positive spillover effects from entrants to incumbents. Both productivity and, to a more limited degree, innovation by entrants is associated positively with the productivity of incumbents in the same region and industry. This finding points to the profound impact entry can have on economic dynamics while also emphasising the additional benefits there may be from innovative entrepreneurship in labor market regions. Third, our results indicate positive correlation between firms' productivity within a region. As such, these findings suggest that industrial policy making should take such interdependent effects into account and be aware that changes in the economic outlook for one sector may also impact the spillovers potential this sector has for others.

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