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Knowledge and Productivity Returns from Types of Innovation: Product versus Process

Master Thesis

MSc Business Economics, Strategy Economics

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Para Elsa.

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Abstract

At some point, an innovative firm needs to decide which specific innovation to conduct. But while the choice is not trivial, theoretical perspectives on the optimal strategy are limited to a determined context and no empirical study has previously faced product innovation against process innovation. As they manifest different affinity with knowledge, they also impact productivity of firms by clear and independent channels. In general terms, product innovation alters or creates demand, meanwhile, process innovation expands supply. To determine which is superior, this research compares knowledge and productivity returns between both types of innovation. The structural nature of an extended CDM model enables the estimation of such returns, moreover, it deals with econometric issues and incorporates modern theoretical insights. Survey data gathered in the MIP is appropriate to estimate each stage of the model, in particular, this research observes German firms of the manufacturing sector from 2013 to 2017. Resulting evidence suggests that product innovation is more responsive to R&D and has a larger impact on productivity compared to process innovation, however, it may be riskier at the same time. Hence, one type is partially superior to the other.

Contents

1. Introduction

The public, firms and most researchers generally associate innovation with a revolutionary product, while it is not incorrect this view is limited to a single manifestation of the phenomenon. Novelties can be introduced in many aspects of organizations and are not necessarily revolutionary, given the inherent uncertainty of innovation, it may be perfectly prudent to introduce discrete improvements or do not introduce any at all. In this sense, firms not only need a strategic plan tailored to its characteristics and objectives but also specific about where to innovate and how to allocate resources efficiently. Conversely, a strategist professional must realize what specific strategy is the most convenient and whether the client is capable of following the corresponding advice. Advising to innovate is not enough, it is mostly expected or obvious, a complete proposal would point the direction towards where to invest resources. This research argues that one fundamental decision is associated with the type of innovation, in other words, whether to introduce a new product or a new process.

Certainly, some firms may introduce multiple types of innovation, but a typical firm would have to choose one at least to start with. Product and process innovation can behave as complements or substitutes depending on market conditions. In economic literature, theoretical approaches suggest that the optimal strategy is not trivial since product innovation affects demand while process innovation affects supply, moreover, the competition regime shape incentives (Bonnano & Haworth, 1996; Mantovani, 2005; Rosenkranz, 2003; Vives, 2008). The Product Life Cycle theory would suggest the optimal strategy is determined by the stage of development (Utterback & Abernathy, 1975), nevertheless, some technological opportunities and sectorial patterns may challenge such a claim (Keppler & Kenneth, 2005). Empirical approaches observe firm level data to analyze the impact of innovation types on productivity, although, they compare each type across geographies (Griffith et al., 2006) or sectors (Mairesse et al., 2005) rather than between themselves. Harrison et al. (2008) conducts an empirical study that explicitly compares the impact of product and process innovation on employment. This research is the first empirical study that compares the impact on productivity (productivity returns) as well as the impact of knowledge investment (i.e., R&D) on innovation types (knowledge returns), hence, the research question is:

How do knowledge and productivity returns differ between product and process innovation?

An answer to this question would indicate the optimal strategy for firms engaged in innovation, it is a simple but clear determination that could lead either to success or avoid failure.

The empirical approach observes information on German manufacture firms gathered by the Mannheim Innovation Panel from 2013 to 2017. This source provides both general and innovation attributes that enable a comprehensive methodology originally described by Crepon et al. (1998) and later extended by other authors (Griffith et al., 2006, Hall et al., 2009). The model consists of a recursive system of equation that resembles the linear perspective of innovation, input impacts output and output impact productivity. The analysis of economic risk as an additional dimension of productivity is an extension proposed by this research. It is assumed that R&D is the main innovation input that firms deliberately use to create knowledge, inputs such as equipment acquisition represents acquisition of knowledge created by others. As mentioned before, this study compares rather than describes types of innovation, criteria correspond to knowledge and productivity returns.

Evidence supports every hypothesis formulated in this research, although it is more convincing for some cases. First, R&D has a larger impact on product innovation compared to process innovation. The reason may be that appropriability and operational incentives favor the former while other inputs may be more relevant for the latter. This finding is robust to methodological determinations and is widely consistent with previous studies. Second, product innovation has a larger impact on productivity compared to process innovation. While the former expands the revenue base, the impact of the latter may be ambiguous as it depends on demand elasticity and strategic concerns. Conclusion are generally robust and aligned with previous evidence. Third, productivity returns from product innovation are more volatile compared to process innovation. As opposed to the latter, the former is usually radical and can bring abnormal returns from a privileged position in the market. In this case evidence is weaker but is also the first in literature since no study had previously analyzed economic risk. Evidence indicates that product innovation is more responsive to R&D and has a larger impact on productivity, however, it is also riskier compared to process innovation. Hence, the conclusion is that product innovation is partially superior.

The present document is structured as an empirical study. In the first section, economical concepts are introduced before each hypothesis is formulated with theoretical and empirical insights. Source, definitions and description of the data are provided in the next section. The third section contains the motivation of the model as well as details of econometric specifications. Results are reported in the fourth section along with robustness check and discussion of previous findings. The last section concludes the findings, notes different kinds of limitations, explains economic implications, and motivates further research.

2. Theoretical Framework

In this section economical and strategic insights on product and process innovation are discussed. Once established the conceptual terms, each hypothesis is formulated on the basis of theoretical conjectures and empirical findings in literature.

2.1. Concepts

Firms conduct different strategies to obtain comparative advantages in the future, some may internationalize, others restructure or perform marketing. Amid modern phenomena, such as technological development and globalization, innovation arises as a paramount strategy. Although there is not an ultimate definition of innovation, this research understands it as the commercialization of an invention (Schumpeter, 1934). While firms are not necessarily inventors, they require specific capabilities and resources to become innovators. Knowledge, the main ingredient, has economic properties that explain most of the success or failure of innovation as a strategy. First, it is an asset because accumulates over time, and second, it is a public good because it cannot be confined. Here the incentive to feed innovation meets the risk of losing a unique intangible asset to the competition. In this way, the nature of innovation opens the door for another valid strategy, imitation.

Despite being old as the market itself, innovation is a relatively a new topic in economics as it was firstly theorized by Joseph Schumpeter beginning the past century. In an attempt to analyze its features economists have proposed a few classifications for innovation. Freeman & Soete (1997) characterizes the revolutionary degree, while a disruptive impact is associated with radical innovations, evolutionary progress defines better incremental innovations.

Also, the perspective on innovation has evolved from the idea of an exogenous factor that transforms technology into economic value – a black box- (Kline & Rosenberg, 1986) to a comprehensive system where different actors (e.g., researchers, creditors, suppliers) interact in a determined environment (e.g., institutions, competition, policy). Despite the perspective, economists agree that firms may transform a combination of input into innovation output, for instance, knowledge generated by R&D can be employed to introduce a new product to the market. Whether innovation input or output impacts economic performance is a long debate in literature. Griliches (1979) proposes an augmented production function where knowledge is a third production factor, along with labor and capital, and is quantified as the accumulation R&D investments. While it partially explains the "residual growth" described by Solow (1957), this theoretical proposal does not account for uncertainty, strategy dynamics, and other inputs apart from R&D. More recent literature suggests that it is innovation output rather than innovation input which has an impact on economic performance of firms. (Hansen & Birkinshaw, 2007; Roper et al., 2008; Crepon et al.,1998).

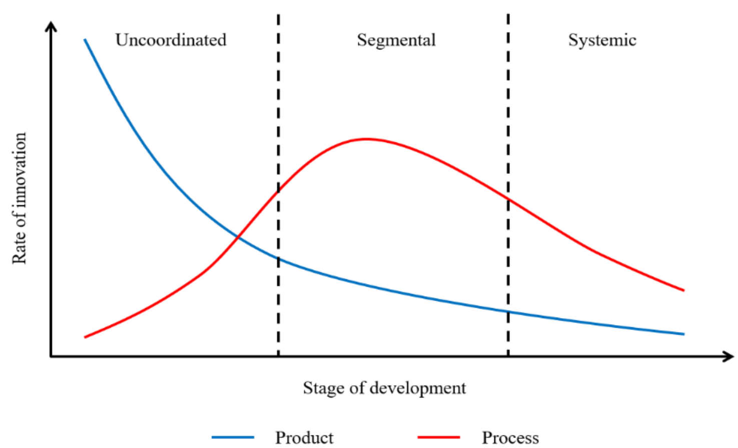
Focusing on the elements subjected to change, Schumpeter (1934) himself distinguishes five types of innovations: new product, new methods of production, new sources of supply, the exploitation of new markets, and new ways to organize business. Later on, this typology was simplified such that the first two types conform technological innovations while the rest are regarded as non-technical innovations (OECD & Eurostat, 2005).

Product innovation refers the introduction of a new or improved product in terms of functionality or quality (OECD & Eurostat, 2005). There are two channels by which this type of innovation impacts productivity of firms. First, a higher willingness to pay resulting from a rotation of demand for improved or differentiated products in the existing market (Kamien & Schwartz, 1982; Beath et al., 1987; Shaked & Sutton, 1982; Vickers, 1986). Second, an expansion of revenue base from the creation of demand in a new market (Beath et al. 1995; Dasgupta & Stiglitz, 1980; Reinganum, 1981). Certainly, revenues from a new product may cannibalize revenues from existing products because not every customer would necessarily substitute the latter for the former. Moreover, the extent to which product innovation increases productivity depends mainly on appropriability conditions since competitors would likely imitate a novel product if the innovative firm is not able to protect the intellectual property (Geroski, 1995; Teece, 1986).

Process innovation refers to the implementation of new or improved methods of production (OECD & Eurostat, 2005). The direct channel which increases productivity consists of an expansion of supply for the existing products as a result of the reduction of marginal costs (Adner & Levinthal, 2001). An indirect channel emerges in the presence of elastic demand, the eventual increase in output yields additional productivity as a result of economies of scale (Mohnen & Hall, 2013). Gopalakrishnan et al. (1999) conclude that subjacent knowledge of this type of innovation is more systemic and complex, therefore, it is not likely to be imitated by competitors. Moreover, the extent to which process innovation increases productivity depends mainly on the ex-ante output size since a unit cost reduction is directly multiplied by the number of units produced when demand is not altered (Keppler, 1996).

This research argues that an innovation strategy involves choosing the combination of technological types of innovation. Although firms may conduct one or both types, or none, several factors may determine the optimal strategy. Findings of Kraft (1990) reveal that product and process innovation are not independent of each other, other studies indicate that the adoption of one drives the eventual adoption of the other (Martinez-Ros & Labeaga, 2009; Miravete & Pernias, 2006). Pisano & Wheelwright (1995) explains that process innovation complements product innovation by accelerating product launch, enabling production ramp-up, enhancing product functionality, and reinforcing appropriability. As much as empirical evidence confirms these dynamics (Oke, 2007; Robin & Schubert, 2013), some literature questions such a strategic complementarity. Weiss (2003) argues that firms favor product innovation when products are close substitutes, while they favor process innovation when the products are widely differentiated. Moreover, the strength of complementarity may also depend on the novelty of the innovations (Reichstein & Salter, 2006). As noted by Karlsson & Travassoli (2016), a typical firm cannot engage in all possible combinations of innovation types due to budget restrictions.

Figure 1: Rate of product and process innovation over developments stages



Note: Adapted from Utterback & Abernathy (1975)

From a Product Life Cycle perspective, Utterback and Abernathy (1975) theorize that the adoption of product and process innovation follow development stages. Figure 1 exhibits the rate of innovation by type over stages of development, the introduction of new products eventually diminishes. Starting at the Uncoordinated stage, primitive technology and undefined preferences encourage firms to introduce a large variety of products through innovation. By the time a certain product becomes predominant, the market enters into the Segmental stage where uncertainty decreases as sufficient demand for the standardized product justifies investments in specialized production, namely process innovation. Finally, the market realizes a predominant production system and the focus on cost minimization, however, further process innovation becomes too costly in such an integrated and standardized system of production. A relevant conjecture of this theory is that the optimal strategy should be formulated in terms of timing rather than complementarity dynamics.

In any case, economic theory and empirical evidence suggest that the optimal innovation strategy is not trivial, the choice among types of technological innovations responds to specific economics incentives and has implications on the productivity of firms.

2.2. Hypotheses formulation

Besides financial performance, projects are driven by institutional factors that may secure returns from investments. In the case of R&D, firm employ intellectual property rights (hereinafter, IPR) to appropriate, protect, and capitalize knowledge. Conversely, incentives to conduct R&D are lower if firms are not able to turn resulting knowledge into legal property. Formal IPR, especially patents, usually protect new product because imitation represents the latent risk of exposure and advertisement in the market (Levin et al., 1987). Process innovation operates within firms, not even customers can witness directly, so informal IPR such as secrecy is preferred over patents (Pisano & Wheelwright, 1995). Compared to product innovation, subjacent technology is also more readily available in the market (Ettlie & Reza, 1992; Teece, 1986). Furthermore, transaction costs of patenting are higher because property rights over process innovation cannot be defined and enforced as easily as those over product innovation (Levin et al., 1987; Lunn, 1986). Hence, property incentives for R&D are higher for product innovation compared to process innovation.

Although studies focus on R&D as the main innovation input, some innovation output is not R&D-based, indeed, firms use a combined variety of innovation inputs (Dosi, 1988). Often process innovation is the result of technology acquisition, in this sense, firms refrain from developing new technology and choose to buy novel machinery and equipment from specialized suppliers (Karlsson & Travassoli, 2015). Empirical evidence indicates product innovation is more associated with internal inputs, such as R&D and training, than with external inputs, such as machinery (Cainelli et al., 2015; Pavitt, 1984). Furthermore, Love & Ropper (1999; 2001) argues that R&D may not be conducted along with external inputs because, on top of budget restrictions (Karlsson & Travassoli, 2016), firms have different managerial practices and incentives that determine their innovation strategy. Those risk adverse and less responsive to the market would engage in long R&D projects, meanwhile, those concerned about innovation lead timing would accelerate developments employing external inputs, namely engaging in external cooperation and technological transfer from related parties (Love &

Ropper, 2001). Hence, R&D is a more conducive input for product innovation than for process innovation.

Even if R&D produces new knowledge (i.e., invention), firms require the capabilities and conditions to commercialize it in the market (i.e., innovation; Fagerberg, 2013). A supply chain is an integrated group of processes that are designed according to the needs and resources of a determined firm, therefore, a revolutionary change in one of them would necessarily have implications of the rest (Tornatzky & Fleischer, 1990). Moreover, process innovation is normally associated with changes in the organizational structures and administrative systems (Ettlie & Reza, 1992). Especially in the later stages of development, production systems become efficient and integrated as much as highly rigid to alterations that might ramify extensively (Abernathy & Utterback, 1978). On the contrary, product innovation is relatively more autonomous as it proceeds along developments stages without requiring major changes in organizational systems (Gopalakrihnan et al., 1999). Rather than firm-specific, new product innovation is industry-specific which explains also why it is more imitable than process innovation. Hence, knowledge generated by R&D is more easily transformed into product innovation than into process innovation.

As an investment, it is argued that R&D may have a different impact on the probability of introducing product and process innovation. While the former provides relatively higher institutional and operational incentives, the latter is relatively more responsive to external input. Therefore, the following hypothesis is formulated:

Hypothesis 1: Knowledge returns from R&D are higher for product innovation than for process innovation.

One of the main conclusions of Product Life Cycle theory, proposed by Utterback & Abernathy (1975) and formalized later by Keppler (1996), is that initial output determines the impact of process innovation on productivity. Because cost reduction decreases marginal costs, it increases revenues as output expands for the same product in the same market. Conversely, even the largest cost saving would not be convenient for firms producing low output since innovation costs may be higher than its net benefits, it may even increase costs (Jamandreu & Mairesse, 2016). Based on the augmented production function theorized by Griliches (1979), Hall (2011) formally models how knowledge impacts revenue from the same market through two channels. Directly by increasing efficiency of production and indirectly by expanding the demand, in a rough sense, these represent process and product innovation respectively. Conjectures reinforce the idea that process innovation has an ambiguous effect on revenues that depends on demand elasticity, meanwhile the effect of product innovation is always positive (Hall, 2011). Hence, product innovation increases revenue in the same market, this does not depend on market power as in the case of process innovation.

Product innovation may create new sources of revenues either by expanding demand on the current market, by capturing customers, or by creating a whole new market (Mohnen & Hall, 2013). Certainly, this would not be a result of process innovation because cost reduction affects efficiency of operations rather than preferences of consumers (Adner & Levinthal, 2001; Kraft, 1990; Eswaran & Gallini, 1996). In strategic terms, Koellinger (2008) describes process innovation as a defensive strategy aimed at increasing market share on existing markets, while product innovation is an attack strategy aimed at entering new markets. Moreover, new products may generate new streams of revenue through licensing of patents (Cohen & Keppler, 1996). As much as new products may cannibalize revenues from old products (Yin & Zuscovitch, 1998), they would compensate through an increase in differentiation (Belleflamme & Peitz, 2015) and could be also complements with old products (Mohnen & Hall, 2013). Hitt et al. (1997) explain that novel products may enable competition in the international market, indeed, exports and product innovation exhibit a virtuous strategical cycle (Golovko & Valentini 2011). From a customer perspective, a theoretical model described by Bhoovaraghavan et al., (1996) suggests that while process innovation satisfies only existing needs, product innovation satisfies both existing needs and new needs. Hence, only product innovation expands revenue base.

Bonanno & Haworth (1998) extends the discussion on the impact of competition on innovation, built on the conflictive conclusions of Schumpeter (1943) and Arrow (1962), by distinguishing by innovation type and competition regime (i.e., Bertrand and Cournot). The conjectures suggest that cost reduction has a negative strategic effect, indeed, it intensifies Bertrand competition. In another theoretical approach, Rosenkranz (2003) analyzes the strategic decisions of identical duopolists that may cooperate in R&D but compete in a market where demand is characterized by preference for variety. One key conclusion is that additional revenues from cost reduction diminish given the negative competitive spillovers of R&D. Hence, process innovation inherits some negative strategical effects on revenues.

As a strategic decision, it is argued that product innovation may have a different impact on productivity compared to process innovation. While the former increases revenue base by expanding existing markets and creating new ones, the latter has an ambiguous impact that depends on market share, competition regime, and other strategic dynamics. Therefore, the following hypothesis is formulated:

Hypothesis 2: Productivity returns from product innovation are larger than those from process innovation.

When a firm introduces a radical product innovation it may not only open a new one but would also become the monopolist by default. Even if competitors eventually spawn, being an innovative first mover provides static and dynamic advantages in terms of market share (Kim & Lee, 2011; Huff & Robinson, 1994). This position confers monopoly rents until competitors imitate the product or introduce a differentiated alternative (Geroski, 1995; Rosernberg & Steinmueller, 1988; Teece, 1986). Bhoovaraghavan et al. (1996) also incorporates these dynamics in their theoretical model, conjectures reveal that followers adopt process innovation as a strategy to compete in a market where the pioneers conducted product innovation. Yin & Zuscovitch (1998) reach similar conclusions from another theoretical perspective which focuses on the relationship between firm size and R&D portfolio. One of their conclusions is that large firms maintain their leadership in the original market by conducting process innovation, meanwhile, monopoly rents are the main incentives for small firms to dominate a new market by introducing a new product. Notably, each of these empirical and theoretical insights are consistent with the Product Life Cycle conjectures proposed by Utterback & Abernathy (1975). Hence, product innovators may perceive abnormal returns as pioneers of a new market while process innovators may at most become followers.

During the early stages of development, there is an uncertainty about performance of diverse products being actively introduced to the market, preferences of consumers are not yet defined, and innovation is driven by market knowledge rather than technology (Abernathy & Utterback, 1978). This context favors small and adaptable firms with flexible operations and quicker response to emerging preferences. Whereas the nature of radical innovation implies replacing or substituting existing products, creative destruction (Schumpeter, 1934), small firms do not face a major risk given their low market share. Consequently, they tend to introduce radical innovations which are uncertain and episodic (Yin & Zuscovitch, 1998). Empirical evidence suggests that innovation is riskier for young firms as it yield unevenly distributed returns, in fact, R&D increases productivity of most productive firms and decreases that of least productive ones (Coad et al., 2016). As technology matures and preferences are defined, firms seek efficiency through improved processes, however, changes are incremental rather than radical because the latter would be costly in integrated systems (Abernathy & Utterback, 1978). But while the technological risk prevails for both product and process innovation, only the latter faces market risk given that the former arises once uncertainty on preferences is resolved. At that point, the predominant product is standardized and offered with slight differences by many competitors (Keppler, 1996). Hence, product innovation is relatively more radical than process innovation.

As a strategic decision, it is argued that product innovation may have a different risk profile compared to process innovation. While the former is may yield abnormal returns related to a privileged position in the market, its radical nature may unfold in absolute failure. Process innovation is rather discrete as it usually brings incremental improvements to integrated systems of production, besides, it is arguably exempt from market risk. Therefore, the following hypothesis is formulated:

Hypothesis 3: Productivity returns from product innovation are more volatile than those from process innovation.

In synthesis, this research finds arguments to claim that product innovation is more sensitive to R&D and would have a larger impact on productivity compared to process innovation, however, it is also more risky.

3. Data

In this section, the source of information is introduced and reasons for its use are explained. Then, definitions of relevant variables are discussed, finally, a quantitative description of the dataset is provided.

3.1. Source

The source of information is the Mannheim Innovation Panel (hereinafter, MIP) which is a business survey prepared and managed by the Leibniz Centre for European Economic Research (hereinafter, ZEW) since 1993. This annual survey is representative for the German firm population, indeed, it is the official German contributor to the Community Innovation Survey (hereinafter, CIS) which is the main source of information of research on innovation in Europe. Designed as a panel, the MIP intends to follow the same firms every year, however, sample size varies over time because some firms might merge or close, conversely, new ones are included. Also, every two years the questionary is refreshed to include relevant variables for research and account for privacy concerns.

Apart from general and financial information, the MIP captures the innovation situation, resources, and performance of German firms. Few public sources have a similar scope on innovation, for instance, the Enterprise Survey prepared by the World Bank contains innovation attributes of firms despite being smaller in sample size and mostly representative of developing countries. The CIS, and other contributing surveys, are only available for professional research.

Given the intangible nature of knowledge and privacy concerns, research on innovation topics normally observes surveys over factual sources such as Orbis, published by Bureau van Dijk. Although some literature observes data related to intellectual property rights, such as those published by the World Intellectual Property Organization (hereinafter, WIPO), this information is not suitable for the present research for two reasons. First, firms often protect product innovation by patenting because it is exposed to the market and thus imitable, meanwhile, process innovation may be announced but is rarely disclosed, so secrecy is more effective (Levin et al., 1987). Therefore, considering intellectual property rights as a measure of innovation output would lead to a measurement error. Second, factual sources such as WIPO normally aggregate information to a sectorial level, this frustrates controlling for firm specific attributes which may lead to biased estimations.

From the available waves between 1993 to 2022 of the MIP, only three were selected: 2013, 2015, and 2017. More recent waves would be subjected to business disruptions originated by the COVID-19 economic crisis, for a similar reason, waves around the financial crisis of 2009 were discarded. As mentioned before, questions of the survey alternate over years or might be discontinued. For the selected waves, questions corresponding to critical variables were present in each of them. Therefore, restricting the time window to the years 2013, 2015 and 2017 undermines the presence of atypical measures and provides a comprehensive set of variables.

Following related literature, only firms in the manufacturing sector were observed. Compared to the rest of the economic sectors, product and process innovation are more clearly distinguished (Hall, 2011, Harrison et al., 2008). These types of innovation might characterize the same phenomena in the service sector, for example, the introduction of online banking could either be framed as a new platform for transactions for the customers as well as a revolutionary system to process transactions by the banks. As a result of this unique filter, a total of 8,551 observations remains in the dataset.

3.2. Definitions

Table 1 reports the type and definition of the variables extracted from the MIP for the selected years. The innovation input measure is captured by *R&D intensity* which is computed as R&D expenditure per full-time employee, it is the most popular measure in related literature despite some exceptions which consider R&D expenditure as a proportion of sales (Aldieri et al., 2019). Observing R&D relative to the size (i.e., number of employees), rather than to sales, is convenient because it provides a stable measure over time and represents better the effort of firms to innovate. Compared those small, large firms possess more financial resources and capabilities such as networks and reputation (Herriot et al., 1984; Levitt & Match, 1988). To avoid a disproportional impact of outliers, this variable is measured in its logarithmic form.

As an innovation output measure, answers to the MIP survey captured by *Product* and *Process*. In an specific question, firms were asked whether they introduced a product innovation during the last three years, similarly for process innovation in a different question. Respondents were informed about the definition of product and process innovation according to the third edition of the Oslo Manual (OECD & Eurostat, 2005), a document accepted by related literature as guideline for collecting and interpreting innovation data. Therefore, this research understands product innovation as:

“The introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness and other functional characteristics (OECD & Eurostat, 2005, p. 48).”

And process innovation as:

“The implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software (OECD & Eurostat, 2005, p. 49).”

Table 1: Definition of variables

Variable	Type	Definition
Year	Categorical	Year of wave
R&D intensity	Continuous	R&D expenditure per employee in EUR (logarithmic form)
Product	Binary	1 if introduced product innovation during the last 3 years
Process	Binary	1 if introduced process innovation during the last 3 years
Innovation	Categorical	Category of innovation combination (product or process)
Productivity	Continuous	Sales per employee in EUR (logarithmic form)
Risk	Binary	1 if productivity is lower than p(10) or higher than p(90)
Structure	Binary	1 if belongs to a group of companies
Age	Categorical	Category of establishment year
Size	Categorical	Category of size based on number of employees
Sector	Categorical	Category of sector
Competition	Binary	1 if threat represented by new competitors is important
Internationalization	Binary	1 if active in the international market
Human capital	Categorical	Category of proportion of employees graduated
Physical capital	Continuous	Tangible assets per employee
Exports	Continuous	Sales from exports as a proportion of sales
Capital intensity	Continuous	Investment cost as proportion of sales
Training	Continuous	Training expenditure as proportion of personnel expense
ICT	Continuous	Software expenditure as proportion of sales
Cooperation	Binary	1 if innovation-related cooperation
Public support	Binary	1 if received public subsidies for innovation projects
Appropriability	Binary	1 if formal intellectual protection is important
Source customers	Binary	1 if customers as source of information is important
Source suppliers	Binary	1 if suppliers as source of information is important
Source competitors	Binary	1 if competitors as source of information is important
Source academy	Binary	1 if academy as source of information is important
Hamper	Binary	1 if lack of qualified personnel or financing is important

The binary variables *Product* and *Process* are combined to generate *Innovation*, a categorical which indicates the combination of such two types. By construction, the categories of the latter variable are: (1) None, (2) Only product innovation, (3) Only process innovation, and (4) Both.

The measure of economic performance is captured by *Productivity* which is computed as sales per employee in euros, it is the most popular measure in related literature despite some exceptions which observe value added per employee (Polder et al. 2009) or total factor productivity (Lin et al., 2016). As explained in the previous section, product innovation generally impacts sales by increasing willingness to pay given the supply of enhanced or new products, meanwhile, the process innovation generally delivers cost reductions that increases the competitiveness of the innovative firm and consequently its sales. To avoid disproportional impact of outliers, the variable is measured in its logarithmic form.

The measure of economic risk is captured by *Riks* which is computed as a binary variable indicating whether economic performance of the firms was extreme, namely lower than the 10^{th} percentile of higher than the 90^{th} percentile in the sample. This criterion is arbitrary since there are no references in relevant literature, indeed, economic risk has not been explored before.

For privacy reasons, some originally continuous variables are reported in intervals in the MIP. For instance, the variable *Age* captures the establishment year of firms grouped in four categories: (2) before 1990, (2) between 1990 and 2000, (3) between 2001 and 2009, and (4) after 2010. A similar case applies to the variable *Human capital*. In the year 2015, questions about source of information were not asked by the MIP survey, therefore, answers in the year 2013 are observed for the firms that participated in both years.

3.3. Description

Table 2 reports the distribution of *Product* and *Process*, around 45% of observations correspond to no innovative firms. Around half of the firms introduced a product innovation while just a third introduced the other type. Only 10% of the observations correspond to only process innovators, moreover, almost 25% reported both types in the same year. Notably, half of product innovators also introduced process innovation. During the rest of the document, only product and process innovators are referred to as product innovators and process innovators, respectively, for simplicity.

Table 3 reports descriptive statistics of continuous and binary variables by categories of *Innovation*. The average *R&D intensity* is 3,755 euros per employee, however, differences are evident across between innovation types. Product innovators spend more than twice compared to process innovators, per employee and on average. Table A1 (see Appendix C) reports descriptive statistics of continuous and binary variables by other categories of *Innovation*. Notably, the average *R&D intensity* of no innovators is higher than process innovators, but also around half compared to multiple innovators.

Figure A1 (see Appendix A) exhibits the distribution of *R&D intensity* by selected categories of *Innovation*, innovation input of product innovators is slightly more dispersed than that of product innovators. Moreover, *R&D intensity* is reported in approximately 31% of observations, the rest is missing information.

Table 2: Distribution of *Product* and *Process*

	Process		
Product	Yes	No	Total
Yes	1,981	1,871	3,852
%	23.17	21.88	45.05
No	848	3,851	4,699
%	9.92	45.04	54.95
Total	2,829	5,722	8,551
%	33.08	66.92	100.00

Notes: Percentages are computed by cell.

As opposed to innovation input, average economic performance and risk are similar between types of innovation. Sales per employees is around EUR 200,000 per employee for product and process innovators. Figure A2 (see Appendix B) exhibits the distribution of *Productivity* by selected categories of *Innovation*, a similar degree of dispersion is also observed. Around 18% of product innovators reported an extreme level of productivity, while the same is true for process innovators, it is below the 20% (theoretical) corresponding to the full sample.

Table A2 (see Appendix D) reports the distribution of *Year* by categories of *Innovation*, while the wave 2015 and 2017 contribute with similar number of observations, around 2,700 each, the wave 2013 is the most popular with almost 3,200. Notably, the distribution of innovation combinations did not change significantly over these years.

Regarding general attributes, Table A3 (see Appendix E) reports the distribution of *Age* by categories of *Innovation*, mature firms are more represented in the sample. Over 2,000 observations correspond to firms established prior to 1990 while the count is less than 700 for those established after 2010. While it is expected to observe few young firms, the stable distribution of innovation pattern across age is noted. Table A4 (see Appendix F) reports the distribution of *Size* by categories of *Innovation*, around 40% of the observations correspond to Micro firms, the smallest size. More than half of those are not innovators, this proportion is below 25% among those firms of the largest size.

Table A5 (see Appendix G) reports the distribution of *Sector* by categories of *Innovation*, the most popular sector is Metals followed by Electrical equipment while the least are Glass/Ceramics and Retail/Automobile. Firms operating in the Electrical equipment and Machinery sector exhibit a similar innovation pattern, yet quite different from the full sample. As mentioned before, around 45% of firms do not innovate at all, this share is less than 25% in such sectors. On the contrary, just 30% of firms operating in the Mining sector introduced at least one type of innovation. Table A6 (see Appendix H) reports the distribution of *Human capital* by categories of *Innovation*, less than 10% of employees hold a university degree for half of the firms. Among the firms with the highest level of *Human capital*, only 6% are process innovators.

Table 3: Descriptive statistics by selected categories of *Innovation*

	Product		Process		Total	
Variable	N	Mean	N	Mean	N	Mean
R&D intensity	887	8.342	239	7.525	2,656	8.231
Product	1,871	1	848	0	8,551	.45
Process	1,871	0	848	1	8,551	.331
Productivity	1,869	12.199	847	12.251	8,517	12.178
Risk	1,869	.175	847	.187	8,517	.203
Structure	1,866	.323	835	.344	8,509	.316
Competition	1,804	.476	804	.491	7,950	.484
Internationalization	1,630	.763	741	.644	7,347	.65
Physical capital	1,069	.09	476	.154	4,855	.138
Exports	1,630	.26	741	.185	7,347	.209
Capital intensity	1,384	.039	640	.051	6,332	.046
Training	1,291	.009	622	.009	6,029	.008
ICT	1,458	.005	681	.005	6,727	.005
Cooperation	1,871	.274	848	.159	8,551	.188
Public support	1,871	.247	848	.153	8,551	.166
Appropriability	1,641	.229	730	.155	7,655	.143
Source customers	1,341	.653	625	.493	6,527	.396
Source suppliers	1,342	.376	621	.44	6,510	.27
Source competitors	1,345	.535	620	.474	6,525	.326
Source academy	1,337	.258	614	.22	6,509	.179
Hamper	1,308	.561	593	.577	5,694	.537

Notes: The sample is split into four sub-samples according to four categories of variable *Innovation*, only subsamples corresponding to the selected categories are reported in this table. The selected categories are "Only product innovation" and Only process innovation". For simplicity, the categories "Only product innovation" and Only process innovation" are referred as "Product" and "Process", relatively.

For some of the remaining general attributes, product and process innovators are similar to the average firm. Around 33% percent belong to a corporation, and half see new competitors as a threat. Nevertheless, product innovators are more active in the international market and report higher *Exports* compared to process innovators. The latter invest in capital 30% more than the former, also, they possess twice *Physical capital*.

Regarding innovation attributes, product and process innovators are similar to the average firm in few. Training costs represent almost 10% of personnel expenditures, investment in informatic and communication technology just 5% of sales, and around 55% of firms attribute a high importance to hampering factors of innovation. Most innovation attributes differentiate types of innovators, for instance, the proportion of product innovators cooperating is almost twice compared to process innovators. On average, 26% of product innovators receive public subsidies and attributes a high importance to formal intellectual protection, this proportion is around 15% in the case of process innovators. Compared to the average firm, each type of innovator relies more on economical agents as sources of information. Compared to 33% of the firms in the full sample, around 50% of product innovators source information from competitors, this also applies for process innovators. The case is similar for academy as a source of information, nevertheless, there are some differences across types on innovation. While product innovators rely more on information from customers (65 vs 50%), process innovators rely more on suppliers (38 vs 44%).

Table A7 (see Appendix I) reports pairwise correlation between continuous and binary variables, correlations are weak with few exceptions. Between the main variables, *R&D intensity* exhibits a positive correlation with *Product*, meanwhile, that with *Process* is negligible. *Productivity* is also positively correlated with *R&D intensity*, nevertheless, correlation is stronger with *Structure* and *Exports*. Notably, only *Capital intensity* is at least weakly correlated with *Risk*. The strong positive correlation between *Public support* and *Cooperation* is also noted.

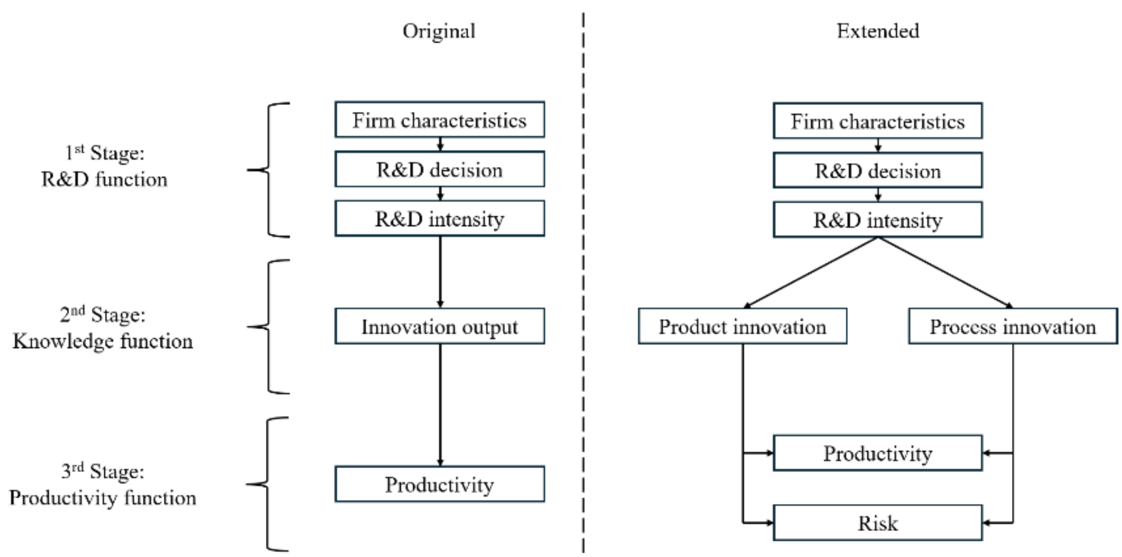
4. Methodology

In this section, the nature of the topic motivates the empirical strategy. Then, the econometrical specifications and hypothesis testing methods are detailed.

4.1. Model

This research applies an extended version of the structural model originally proposed by Crepon et al. (1998, hereinafter CDM) which estimates the relationship between innovation input, innovation output, and productivity through a set recursive system of equations. The main claim of this methodology is that rather than innovation input, it is innovation output which has an impact on productivity. Figure 2 exhibits the stages of the CDM model, the first stage (R&D function) estimates innovation input as the decision and intensity of R&D. In the second stage (Knowledge function), predicted values of *R&D intensity* are included in the estimation of general innovation output, finally, the predicted values of innovation output are used to estimate productivity in a third stage (Productivity function). In practical terms, the extended version of the CDM model distinguishes types of innovation output and considers a second dimension of productivity that captures economic risk. Details of the econometric specification, empirical methods, and insights from the extensions are discussed later in this section.

Figure 2: Stages of the original and extended CDM model



As illustrated by Figure 2, the CDM model resembles the linear perspective of innovation (Kline & Rosenberg, 1986), besides, it was originally proposed to deal with two econometric issues in empirical research which directly estimated the impact of R&D intensity on productivity. First, a few firms report or formally conduct knowledge investments (i.e. R&D), although, many more exert innovation effort (e.g., technology acquisition) or leverage on capabilities (e.g., ideas from employees) that eventually deliver innovation output. An estimation restricted to reporting firms is potentially affected by selection bias because unobserved firms may be systematically different. For instance, larger firms possess those financial resources, assets, and capabilities (e.g., networks) required to launch R&D projects (Abel & Blanchard, 1986; Herriot et al., 1984; Levitt & Match, 1988), moreover, they are generally subjected to accountability policies that require declaring and reporting intangible assets and investments. Second, and most importantly, there are endogeneity issues underlying the linear perspective of innovation which describes a one-way causality from innovation input to innovation output, and from innovation output to productivity. For instance, the introduction of a new product is itself an incentive for further investment in R&D because firms learn from a new generation of knowledge and build absorptive capacity (Cohen & Levinthal, 1989; David, 1992; Stiglitz, 1987). Similarly, large profits of highly productive firms may be reinvested in knowledge or technologies that subsequently feed innovation (Griliches, 1979).

4.2. Econometric specifications

The CDM model is structured in three stages that reflect the linear perspective of innovation. Since its publication, many authors have extended the original stages by modifying the econometric specifications and models. This research integrates those extensions aligned with the nature of the data, relevant assumptions, and the formulated hypotheses.

First stage: R&D function

This stage estimates equations related to innovation input. Equation 1 (hereinafter, the Selection equation) models the decision of firms to invest in R&D.

$$s_i = \begin{cases} 1, & if\ s_i^* = X_i\Lambda + \delta_\mathrm{i} > \tau \\ 0, & otherwise \end{cases} \tag{1}$$

Where s_i denotes the observed decision to invest in R&D and equals 1 if the firm i reports a positive *R&D intensity*. A latent variable denoted by s_i^* such that firm i decides to invest in R&D if it is above a certain threshold τ.

Vector X_i denotes those characteristics of firm i explaining the decision to invest in R&D. Belonging to a corporation (*Structure*) is included because knowledge resources transferred among subsidiaries may enable R&D projects (Love & Ropper, 2001). The exporting strategy (*Exports*) has a symbiotic relationship with the innovation strategies because new markets often demand new products (Golovko & Valentini, 2011). Given the risk of R&D projects, firms would be more likely to invest if they are financially assisted (*Public support*). As an incentive to conduct R&D, effective appropriability conditions (*Appropriability*) secure returns on innovation effort (Spence, 1984). Intuitevely, a perceived obstacle for innovation (*Hamper*) would frustrate the determination to conduct R&D. Sectorial patterns and time fixed effects are controlled by including the variables *Sector* and *Year*, respectively.

Equation 2 (hereinafter, the Intensity equation) models *R&D intensity* of firms.

$$r_i = \begin{cases} \Upsilon_i \Phi + \varepsilon_\mathrm{i}, & if\ s_i = 1 \\ 0, & if\ s_i = 0 \end{cases} \tag{2}$$

Where r_i denotes expenditure as a proportion of sales of firm i (*R&D intensity*) and is positive conditional to the decision to invest in R&D. Vector Υ_i denotes those characteristics of firm i explaining its *R&D intensity*. Except for *Size*, these characteristics are the same as those denoted by the vector X_i.

The error terms of Equation 3 and 4 are denoted by ν and ω, respectively. It is assumed that they follow a bivariate normal distribution with zero mean, unit variance, and a determined correlation. Given the nature of the dependent variables and the latter assumption, this stage is estimated in two steps following the selection model described by Heckman (1979). First, a Probit estimation of Equation 1, and second, an Ordinary Least Squares (hereinafter, OLS) estimation of Equation 2 that includes the Inverse Mill's Ratio (hereinafter, IMR) derived from the first step. A significant coefficient associated to IMR would be evidence of correcting for the potential selection bias discussed previously in this section.

The absence of *Size* in vector Υ_i represents the exclusion condition required to correctly identify the estimation. If such a condition is not valid, then an OLS estimation would be more reliable than a selection model (Wolfolds & Siegel, 2018). As opposed to small firms, the large justify their decision to conduct a risky investment such as R&D by averaging a fixed cost (i.e. sunk costs) over a larger output (Sutton, 1991; Cohen & Keppler, 1996). While the size determines the decision to conduct R&D, it does not determine the level of *R&D intensity* because the relationship between R&D expenditures and number of employees should not necessarily increase or decrease. A larger firm employs, by definition, many workers and has abundant resources to finance large R&D expenditures, however, it should not necessarily be more intensive in R&D compared to a small firm which employs less workers.

Schumpeter (1943) and Galbraith (1957) argue that larger firms are more intensive in R&D because they are able to secure finance for R&D risky projects and possess those assets that complement innovation input. However, Cohen et al. (1987) provide empirical evidence that contradicts such a conjecture, indeed, they show that size does not explain *R&D intensity* but does explain the decision to conduct such an investment. In their perspective, previous considerations ignore the heterogenous technological opportunities and appropriability conditions across sectors. Furthermore, most related literature uses the same variable for the exclusion condition (Aboal & Tacsir, 2018; Alvarez et al., 2010, Fedyunina & Radosevic, 2022; Grifith et al., 2006; Lin et al., 2016; Masso & Vhater, 2006; Peters, 2007; Tevdovski et al., 2017; Wadho & Chaudhry, 2022). Nevertheless, other studies disregard an exclusion condition at all (Aldieri et al. 2019; Baumann & Kritikos, 2016; Hall & Sena, 2014; Hall et al., 2009; Hall et al., 2013; Loof & Heshmati, 2001; Loff et al., 2001; Martin & Uyen, 2015; Mairesse et al., 2005; Polder et al., 2009; Younas & Ul Husnain, 2022).

Second stage: Knowledge function

This stage estimates equations related to innovation output. Equation 3 and 4 models the introduction of product and process innovation by firms, respectively.

$$d_i = \begin{cases} 1, & if\ d_i^* = \beta_d r_i^{\mathrm{p}} + Z_i \Psi_{\mathrm{d}} + \nu_i > 0 \\ 0, & otherwise \end{cases} \tag{3}$$

$$c_i = \begin{cases} 1, & if\ c_i^* = \beta_c r_i^{\mathrm{p}} + Z_i \Psi_c + \omega_i > 0 \\ 0, & otherwise \end{cases} \tag{4}$$

Where d_i indicates whether firm i introduced a product innovation during the last 3 years (*Product*), and c_i indicates the case for process innovation (*Process*). A latent variable denoted by d_i^* such that firm i introduces a product innovation if it is positive, c_i^* denotes the case for process innovation.

The predicted values of r_i resulting from the estimation of Equation 2 are denoted by r_i^{p}. Their inclusion in Equations 3 and 4 are equivalent to an instrumentalization of innovation input which would mitigate the endogeneity issues discussed previously in this section. In the original CDM model, innovation output is measured by patent applications, however, innovation output is not necessarily always protected by patents or any formal intellectual property right. As discussed before, process innovation is rarely patented, indeed, firms would prefer informal intellectual protection such as secrecy (Levin et al., 1987). Therefore, the extended CDM model exploits survey information by observing whether innovation is introduced rather than if it is protected.

Vector Z_i denotes those characteristic of firm i explaining innovation output. R&D is the innovation input by excellence because it is a direct investment on knowledge, however, firms employ several resources of three types. Regarding the internal, trained personnel (*Training*) enhance capabilities and motivation (Sarkis et al. 2010). As an external resource, cooperating with other firms and institutions (*Cooperation*) increases the success of innovation because it combines experiences and expands networks (Sing & Fleming, 2010). Firms also may obtain information from multiple external sources, for instance, feedback from customers (*Source customers*) is likely to drive product innovation. Because they are acquainted with the technology, suppliers (*Source suppliers*) would be a convenient source to improve processes. Moreover, knowledge spills from the interaction with competitors (*Source competitors*) while the academy (*Source academy*) can deliver complex knowledge. R&D activities also require hybrid resources which are developed outside but employed inside the firm. Exclusive equipment for development purposes, such as laboratories, is acquired as fixed assets (*Capital intensity*). Implementing information and communication technologies (*ICT*), such as artificial intelligence, brings efficiency and new knowledge to research. Sectorial patterns and time fixed effects are controlled by including the variables *Sector* and *Year*, respectively.

The error terms of Equation 3 and 4 are denoted by ν and ω, respectively. It is assumed that they follow a bivariate normal distribution with zero mean, unit variance, and a determined correlation. Given the nature of the dependent variables and the latter assumption, a Bivariate Probit model estimates Equation 3 and 4 simultaneously as in Robin & Mairesse (2005). The authors extend the second stage of the original CDM model by distinguishing type of innovation, moreover, they implement a Bivariate Probit to account for the correlation between ν and ω. Compared to independent Probit estimations of each equation, the coefficients estimated by Bivariate probit are more efficient (Cameron & Trivedi, 2005). Another advantage of this model is that it can predict the probability of any combination of innovations, therefore, it is possible to isolate and thus compare the impact of each innovation type on productivity.

Hypothesis 1 is tested by conducting a one-tail significance t-test on the following expression:

$$M.E.\left(d[r_i^{\mathrm{p}}]\right) - M.E.\left(c[r_i^{\mathrm{p}}]\right) = 0$$

Where $M.E.\left(d[r_i^{\mathrm{p}}]\right)$ and $M.E.\left(c[r_i^{\mathrm{p}}]\right)$ denote the marginal effect, at means, of *R&D intensity* on the likelihood of introducing a product and process innovation, respectively. Because these effects represent the yield of an investment in knowledge, they are referred as knowledge returns. A positive and significant estimate would confirm that knowledge returns from R&D are higher for product compared to process innovation.

Third stage: Productivity function

This stage estimates the equations related to productivity. Equation 6 and 7 model economic performance and economic risk of firms, respectively.

$$y_i = \pi_y d_i^{\mathrm{p}} + \varphi_y c_i^{\mathrm{p}} + \lambda_y b_i^{\mathrm{p}} + W_i \Omega_{\mathrm{y}} + \upsilon_i \tag{6}$$

$$m_i = \begin{cases} 1, if\ m_i^* = \pi_m d_i^{\mathrm{p}} + \varphi_m c_i^{\mathrm{p}} + \lambda_m b_i^{\mathrm{p}} + W_i \Omega_{\mathrm{m}} + \sigma_i > 0 \\ 0,\ otherwise \end{cases} \tag{7}$$

Where y_i denotes sales per employee of firm i (*Productivity*). This research extends the original CDM model by introducing a second dimension of productivity, m_i indicates whether *Productivity* of firm i is either greater than the 90th percentile or lower than the 10th percentile of the sample distribution (*Risk*). A latent variable denoted by m_i^* such that *Productivity* of firm i is extreme if it is positive. By estimating the impact of innovation output on *Risk*, this research intends to explore the economic risk of innovation strategies.

The predicted values of d_i resulting from the estimation of Equation 3 are denoted by d_i^{p}. Note that these values correspond to the predicted probability of introducing only a product innovation, the same applies to the predicted values of c_i resulting from the estimation of Equation 4, denoted by c_i^{p}. Following the extension described by Mairesse & Robin (2008) and leveraging on the probabilistic models of the second stage, the predicted probability of introducing both types of innovation, denoted by b_i^{p}, is also included in Equation 6 and 7.

The inclusion of predicted values in these equations is equivalent to an instrumentalization of innovation output which would mitigate the endogeneity issues discussed previously in this section. Following the extension described by Griffith et al. (2006), predicted probabilities of innovation output are computed for all firms in the sample, including those not reporting *R&D intensity* or any innovation output. Because knowledge is a public good within a firm, these authors argue that unreported innovation effort may lead to unreported innovation output.

Vector W_i denotes a set of characteristics of firm i explaining economic performance and risk. Following the Cobb-Douglas production function, *Physical capital* is the main driver of output per unit of labor, it is included in a quadratic form to account for decreasing marginal returns. Besides, the degree of competition (*Competition*) is another determinant since there are economic incentives to produce less in concentrated markets. Bonnano & Haworth (1996) argue that Bertrand competition, which renders a more competitive markets, deters process innovation given its negative strategic effect. Firms active in the international market (*Internationalization*) are more productive because they learn abroad and diversify revenues.

The error terms of Equation 5 and 6 are denoted by υ and σ, respectively. There are no relevant assumptions regarding the bivariate distribution of such error terms, therefore, an OLS and a Logistic model estimates Equation 5 and 6, respectively and independently.

Hypothesis 2 is tested by conducting a one-tail significance t-test on the following expression:

$$\pi_y - \varphi_y = 0$$

Where π_y and φ_y denote the effect of introducing only product and only process on *Productivity*, respectively. Because these effects represent the yield of an investment of productivity, they are referred as productivity returns. A positive and significant estimate would confirm that productivity returns from product innovation are higher compared to those from process innovation.

Finally, Hypothesis 3 is tested by conducting a one-tail significance t-test on the following expression:

$$M.E.\left(d_i^{\mathrm{p}}\right) - M.E.\left(c_i^{\mathrm{p}}\right) = 0$$

Where $M.E.\left(d_i^{\mathrm{p}}\right)$ and $M.E.\left(c_i^{\mathrm{p}}\right)$ denote the marginal effect at means of introducing product and process on the *Risk*, respectively. A positive and significant estimate would confirm that productivity returns from product innovation are more volatile compared to those from process innovation.

5. Results

This section reports and interprets the results of applying the methodology on the data discussed in the previous sections. After testing the hypotheses, results are subjected to multiple robustness checks and discussed employing theoretical and empirical insights.

5.1. Hypotheses testing

Table 5 reports the estimation results from the Heckman selection model estimation of *R&D intensity*, this corresponds to the 1^{st} stage (R&D function) of the extended CDM model. Similar to the rest of the estimations reported in this section, the number of observations is not equal to the total observed in the dataset (i.e., 8,551) due to missing values for some variables. Column 1 reports the results of the selection equation, categories of *Size* are jointly significant, indeed, every firm size larger than "Micro" significantly increases the likelihood of engaging in R&D. Among general attributes, belonging to a corporate group and exports intensity has a significant effect in the same direction. Among knowledge attributes, a positive and significant impact also results from receiving public support for innovation, endorsing intellectual protection, and perceiving factors hampering innovation. Column 2 reports the results for the intensity equation, every attribute has a positive and significant effect on *R&D intensity*, except for *Hamper*.

The exclusion variable and the Mill's Ration are both significant, hence, evidence suggests selection bias about *R&D intensity*. In other words, reporting or conducting R&D is not random, larger firms are more likely to do it compared to smaller firms. Figure A3 (see Appendix J) exhibits the distribution of observed and predicted values of *R&D intensity*, the mean and dispersion of the latter are larger than the former.

Table 6 reports the estimation results from the Bivariate probit estimation of *Product* and *Process*, these correspond to the 2^{nd} stage (knowledge function) of the extended CDM model. Every estimation includes the predicted values of *R&D intensity* computed in the 1^{st} stage (R&D function). Columns 1 and 2 report the coefficients from the Bivariate probit estimation of the probability of introducing product innovation and process innovation, respectively. The correlation between the error terms from the estimations is positive and significant.

Column 3 and 4 report the marginal effects on the probability of introducing only product innovation and only process innovation, respectively. On average, an increase in 1% of R&D expenditure per employee increases the probability of introducing product innovation by 9.4 percentage points (hereinafter, p.p.), ceteris paribus and at a 1% significance level. However, it increases the probability of introducing process innovation by 2.3 p.p., ceteris paribus and at a 5% significance level. By comparing the latter effects, an increase in 1% of R&D intensity increases more the probability of introducing product compared to process innovation by 11.7 p.p., ceteris paribus and at a 1% significance level. Hence, evidence supports Hypothesis 1, knowledge returns from R&D are larger for product innovation compared to process innovation. In other words, introducing a new product is cheaper in terms of R&D.

Table 5: Heckman selection model estimation of *R&D intensity*

Variables	Selection (1)	Intensity (2)
Size (Small)	0.127**	
	[0.061]	
Size (Medium)	0.182***	
	[0.067]	
Size (Large)	0.338***	
	[0.071]	
Size (Corporate)	0.504***	
	[0.082]	
Structure	0.107**	0.165**
	[0.054]	[0.078]
Exports	0.779***	1.123***
	[0.089]	[0.174]
Public support	1.067***	1.003***
	[0.055]	[0.162]
Appropriability	0.963***	0.893***
	[0.064]	[0.199]
Hamper	0.129***	0.044
	[0.043]	[0.066]
Constant	-1.947***	5.260***
	[0.130]	[0.589]
Inverse Mill's Ratio	0.809***	
	[0.262]	
Observations	3,087	3,087

* Significant at 10%, **significant at 5%, and *** significant at 1% for two-tailed test. Standard errors in brackets.
Notes: Reference category of *Size* is "Micro". Categories of the variable *Size* are jointly significant. Variables *Age*, *Sector*, and *Year* are included in every estimation but not reported.

Regarding other innovation inputs, higher capital intensity, additional training, cooperating and sourcing information from customers, suppliers and competitors significantly increases the likelihood of introducing each type of innovation. Moreover, sourcing information from academy only significantly increases the likelihood of introducing process innovation. Finally, additional investment in information and communication technology does not have a significant effect on either.

Figure A4 (see Appendix K) exhibits the predicted values of introducing only product innovation and only process innovation over the predicted values of *R&D intensity*, the relationship between the two latter is apparently negative.

Table 7 reports the results from the OLS estimation of *Productivity* and Logistic estimation of *Risk*, these correspond to the 3rd stage (productivity function) of the extended CDM model. Every estimation includes the predicted values of introducing only product innovation, only process innovation, and both innovations computed in the 2nd stage (knowledge function).

Column 1 reports the coefficients of the OLS estimation of *Productivity*, introducing both type of innovations is the only combination with a positive and significant effect. On average, introducing product innovation increases sales per employee by 15.6% ceteris paribus, however, this effect is not significant. Introducing process innovation has a negative effect of 60%, ceteris paribus and at a 1% significance level. By comparing the latter effects, introducing product innovation increases *Productivity* more than introducing process innovation by 182 p.p., ceteris paribus and at a 1% significance level. Hence, evidence supports Hypothesis 2, productivity returns from product innovation are larger compared to process innovation. In other words, introducing a new product is more profitable.

Regarding other economic drivers, being active in the international market has a positive and significant effect while the degree of competition has a significant effect in the opposite direction. The coefficients associated with the linear and quadratic form of *Physical capital*, both significant, depict the decreasing marginal returns of capital.

Column 3 reports marginal effects corresponding to the Logistic estimation of *Risk*, no combination of innovation has a significant effect. On average, product innovation increases the likelihood of extreme levels of sales per employee by 2.5 p.p. ceteris paribus, however, this effect is not significant. Process innovation has a negative effect of 33.2 p.p. ceteris paribus, also not significant. By comparing the latter effects, product innovation increases *Risk* more than process innovation by 35.7 p.p., ceteris paribus and at a 10% significance level. Hence, evidence supports Hypothesis 3, productivity returns from product innovation are more volatile compared to those from process innovation. In other words, introducing a new product is more risky.

Table 6: Bivariate probit estimation of *Product* and *Process*

Variables	Product (1)	Process (2)	Product (3)	Process (4)
Predicted R&D intensity	0.509***	0.238***	0.094***	-0.023**
	[0.050]	[0.045]	[0.015]	[0.010]
Capital intensity	0.589*	1.030***	-0.026	0.107*
	[0.315]	[0.284]	[0.093]	[0.061]
Training	6.858***	5.620***	0.838	0.120
	[1.888]	[1.743]	[0.563]	[0.368]
ICT	3.046	2.781	0.321	0.104
	[2.747]	[2.351]	[0.806]	[0.512]
Cooperation	0.445***	0.242***	0.068***	-0.019
	[0.084]	[0.073]	[0.025]	[0.015]
Source customers	0.849***	0.617***	0.101***	-0.006
	[0.059]	[0.056]	[0.017]	[0.011]
Source suppliers	0.400***	0.480***	0.008	0.027**
	[0.064]	[0.057]	[0.018]	[0.013]
Source competitors	0.454***	0.199***	0.083***	-0.025**
	[0.063]	[0.057]	[0.019]	[0.012]
Source academy	-0.019	0.176**	-0.037*	0.035**
	[0.079]	[0.069]	[0.022]	[0.016]
Constant	-4.644***	-3.027***		
	[0.319]	[0.289]		
ρ	0.524***			
	[0.030]			
Log-likelihood	-3,032	-3,032		
H1			0.117***	
			[0.018]	
Observations	3,204	3,204	3,204	3,204

* Significant at 10%, **significant at 5%, and *** significant at 1% for two-tailed test. Standard errors in brackets.
Notes: The variable *Predicted R&D intensity* refers to the predicted values of *R&D intensity*. Columns 1 and 2 report coefficients from the estimation of *Product* and *Process*, respectively. Column 3 and 4 report marginal effects on the predicted probability of introducing only product innovation and only process innovation, respectively. Marginal effects are reported at means of continuous variables, and at the reference category of binary and categorical variables. Variables *Human capital*, *Age*, *Sector*, and *Year* are included in every column but not reported. In every column, categories of the variable *Human capital* are not jointly significant.

Regarding other economic drivers, and contrary to the other dimension of productivity, the degree of competition has a positive and significant effect while being active in the international market has a significant effect in the opposite direction. Similar to *Productivity* itself, *Risk* increases in *Physical capital* at a decreasing rate.

Table 7: Ordinary Least Squares estimation of *Productivity* and Logistic estimation of *Risk*

Variables	Productivity (1)	Risk (2)	Riks (3)
Predicted Product	0.145	0.168	0.025
	[0.139]	[0.626]	[0.093]
Predicted Process	-0.891***	-2.229	-0.332
	[0.319]	[1.379]	[0.205]
Predicted Both	0.123*	-0.354	-0.053
	[0.064]	[0.295]	[0.044]
Competition	-0.067***	0.184*	0.027*
	[0.025]	[0.107]	[0.016]
Internationalization	0.412***	-0.768***	-0.126***
	[0.032]	[0.131]	[0.023]
Physical capital	1.185***	1.939***	0.280***
	[0.097]	[0.378]	[0.055]
Physical capital^2	-0.254***	-0.277***	
	[0.027]	[0.107]	
Constant	11.970***	-0.871***	
Log-likelihood	-2,335	-1,141	
H2	1.036***		
	[0.383]		
H3			0.357*
			[0.252]
Observations	2,534	2,534	2,534

* Significant at 10%, **significant at 5%, and *** significant at 1% for two-tailed test. Standard errors in brackets.

Notes: Variables *Predicted Product* and *Predicted Process* refer to the predicted values of introducing only product innovation and only process innovation, respectively. The variable *Predicted Both* refers to the predicted probability of introducing both product and process innovation. Columns 1 and 2 report coefficients from the estimation of *Productivity* and *Risk*, respectively. Columns 3 reports marginal effects on *Risk* at means of continuous variables, and at the reference category of binary and categorical variables. Variables *Age*, *Sector*, and *Year* are included in every column but not reported.

In synthesis, empirical evidence from German firms between 2013 and 2017 supports each hypothesis formulated by this research. Knowledge returns are higher for product innovation, same for productivity returns but these are more volatile compared to process innovation.

5.2. Robustness checks

Cabagnols and Le Bas (2002) apply a Multinomial Logit in the 2nd stage (knowledge function) of the extended CDM model. As opposed to the Bivariate probit, such a method does not account for the correlation between the error terms of the outcomes, however, it isolates the effect of *R&D intensity* on each combination of innovation as individual outcomes (see Appendix L). In this way, knowledge returns can be more precisely compared.

Table 8: Results by using Multinomial Logit to estimate *Product* and *Process*

	Product	Process	Productivity	Risk
Variables	(1)	(2)	(3)	(4)
Predicted R&D intensity	0.093***	-0.011		
	[0.017]	[0.014]		
Predicted Product			0.315**	-0.017
			[0.149]	[0.099]
Predicted Process			-0.710***	-0.280*
			[0.248]	[0.166]
Predicted Both			0.136	0.010
			[0.088]	[0.061]
Constant			11.933***	
			[0.074]	
H1	0.104***			
	[0.022]			
H2			1.025***	
			[0.333]	
H3				0.263
				[0.223]
Observations	3,204	3,204	2,534	2,534

* Significant at 10%, **significant at 5%, and *** significant at 1% for two-tailed test. Standard errors in brackets.
Notes: Columns 1, 2 and 4 report marginal effects at means of continuous variables, and at the reference category of binary and categorical variables. Column 1 and 2 report marginal effects on the predicted probability of introducing only product innovation and only process innovation, respectively. Variables *Capital intensity*, *Training*, *ICT*, *Cooperation*, *Source customers*, *Source suppliers*, *Source competitors*, *Source academy*, and *Human capital* are included in column 1 and 2 but not reported. Variables *Competition*, *Internationalization*, *Physical capital* and *Physical capital^2* are included in column 3 but not reported. Variables *Competition*, *Internationalization*, and *Physical capital* are included in column 4 but not reported. Variables *Age*, *Sector*, and *Year* are included in every column but not reported.

Table 8 reports the main results discussed in the previous subsection by using Multinomial Logit in the 2nd stage of the extended CDM model. Columns 1 and 2 report the marginal effects on the probability of introducing product and process innovation, respectively, *R&D intensity* has a positive and significant effect only on the former. The effect on product innovation is significantly larger than on process innovation, hence, evidence supports Hypothesis 1 and is consistent with the main results. Column 3 reports the coefficients of the OLS estimation of *Productivity*, product innovation has a positive effect while process innovation has a negative effect, both are significant. The former effect is significantly larger than the latter, hence, evidence supports Hypothesis 2 and is consistent with the main results. Column 4 reports the marginal effects on Risk, process innovation has a negative and significant effect. Also, the effect of product innovation is not significantly larger than that of process innovation, hence, evidence does not support Hypothesis 3 and is not consistent with the main results.

Table 9: Results by excluding firms established before 1990 from the sample

	Product	Process	Productivity	Risk
Variables	(1)	(2)	(3)	(4)
Predicted R&D intensity	0.078***	-0.022**		
	[0.015]	[0.010]		
Predicted Product			-0.211	0.089
			[0.177]	[0.114]
Predicted Process			-0.780*	-0.360
			[0.420]	[0.271]
Predicted Both			0.036	-0.057
			[0.089]	[0.059]
Constant			12.086***	
			[0.095]	
H1	0.100***			
	[0.018]			
H2			0.387	
			[0.570]	
H3				0.449*
				[0.321]
Observations	1,815	1,815	1,442	1,442

* Significant at 10%, **significant at 5%, and *** significant at 1% for two-tailed test. Standard errors in brackets.
Notes: Columns 3 reports coefficients of the estimation. Column 1, 3 and 4 report marginal effects at means of continuous variables, and at the reference category of binary and categorical variables. Column 1 and 2 report marginal effects on the predicted probability of introducing only product innovation and only process innovation, respectively. Variables *Capital intensity, Training, ICT, Cooperation, Source customers, Source suppliers, Source competitors, Source academy*, and *Human capital* are included in column 1 and 2 but not reported. Variables *Competition, Internationalization, Physical capital* and *Physical capital^2* are included in column 3 but not reported. Variables *Competition, Internationalization*, and *Physical capital* are included in column 3 but not reported. Variables *Age, Sector*, and *Year* are included in every column but not reported.

Product life cycle theory suggests that mature firms are more likely to introduce different types of innovation, or at least being capable of choosing, because they possess more resources and experience. Conversely, young firms are more likely to focus only on product innovation because they face less concerns related to product cannibalism and standardization (Utterback & Abernathy, 1975). Among the four categories of *Age* the most typical is "Before 1990", around 40% of firms in the sample have at least 20 years in the market (see Appendix E). Implications of economic theory suggest that conclusions might be biased by the disproportional representation of mature firms in the sample.

Table 10: Results by including only firms observed in every wave in the sample

Variables	Product (1)	Process (2)	Productivity (3)	Risk (4)
Predicted R&D intensity	0.214***	-0.052*		
	[0.046]	[0.031]		
Predicted Product			0.083	-0.065
			[0.213]	[0.140]
Predicted Process			-0.704	0.020
			[0.477]	[0.294]
Predicted Both			0.183*	-0.060
			[0.106]	[0.072]
Constant			12.193***	
			[0.152]	
H1	0.265***			
	[0.056]			
H2			0.787*	
			[0.562]	
H3				-0.085
				[0.352]
Observations	983	983	810	810

* Significant at 10%, **significant at 5%, and *** significant at 1% for two-tailed test. Standard errors in brackets.
Notes: Columns 3 reports coefficients of the estimation. Column 1, 3 and 4 report marginal effects at means of continuous variables, and at the reference category of binary and categorical variables. Column 1 and 2 report marginal effects on the predicted probability of introducing only product innovation and only process innovation, respectively. Variables *Capital intensity*, *Training*, *ICT*, *Cooperation*, *Source customers*, *Source suppliers*, *Source competitors*, *Source academy*, and *Human capital* are included in column 1 and 2 but not reported. Variables *Competition*, *Internationalization*, *Physical capital* and *Physical capital^2* are included in column 3 but not reported. Variables *Competition*, *Internationalization*, and *Physical capital* are included in column 3 but not reported. Variables *Age*, *Sector*, and *Year* are included in every column but not reported.

Table 9 reports the main results discussed in the previous subsection by excluding mature firms from the sample. Columns 1 and 2 report the marginal effects on the probability of introducing only product and only process innovation, respectively, *R&D intensity* has a positive effect on product innovation while a negative effect on process innovation, both are significant. The effect on the former is significantly larger than on the latter, hence, evidence supports Hypothesis 1 and is consistent with the main results. Column 3 reports the coefficients of the OLS estimation of *Productivity*, product and process innovation have a negative effect. The former effect is not significantly larger than the latter, hence, evidence does not support Hypothesis 2 and is inconsistent with the main results. Column 4 reports the marginal effects on *Risk*, neither product nor process innovation had a significant effect. However, the former is significantly larger than the latter, hence, evidence supports Hypothesis 3 and is consistent with the main results.

As an attempt to account for lagged effects and attrition bias, Peters (2007) restricts the CIS dataset to those firms observed in three consecutive waves. Table A8 (see Appendix M) reports the panel pattern in the data, only 13.3% of the firms in the sample are observed every year. Given that the panel is highly unbalanced, attrition arises as a potential source of bias. Observing a balanced panel would account for such a source of bias despite potentially introducing selection bias.

Table 10 reports the main results discussed in the previous subsection for a balanced panel. Columns 1 and 2 report the marginal effects on the probability of introducing only product and only process innovation, respectively, *R&D intensity* has a positive effect on product innovation and a negative effect on process innovation, both are significant. The effect on the former is significantly larger than on the latter, hence, evidence supports Hypothesis 1 and is consistent with the main results. Column 3 reports the coefficients of the OLS estimation of *Productivity*, product innovation has a positive effect while process innovation has a negative effect, none is significant. The former effect is significantly larger than the latter, hence, evidence supports Hypothesis 2 and is consistent with the main results. Column 4 reports the marginal effects on *Risk*, neither product nor process innovation had a significant effect. Notably, the former is smaller than the latter, hence, evidence does not support Hypothesis 3 and is inconsistent with the main results.

In synthesis, conclusions about Hypothesis 1 and 2 are robust to data and methodology choices, however, conclusions about Hypothesis 3 are not. There is strong evidence suggesting that knowledge and productivity returns are higher for product innovation.

5.3. Discussion

Hall (2011) reports a comprehensive review of studies applying a similar extended version of CDM model. These and other recent studies do not compare product and process innovation, nevertheless, it is possible to derive partial conclusions from their empirical evidence regarding hypotheses tested in this research. Since marginal effects cannot be statistically compared without unreported information (i.e., covariance matrix), difference in rough magnitudes is used to discuss the findings of previous studies with this research.

From the pool of empirical studies applying a similar methodology, this discussion only considers those estimating the same extended version of CDM model and observing firms in developed countries. Also, some studies are discarded because of the different operationalization of the main variables (Aldieri et al., 2019; Masso & Vhater, 2008). Notably, no study observes firms over the period corresponding to this research, indeed, every previous evidence dates before 2012. The research by Baumann & Kritikos (2016) is arguably the most similar to the present one. It observes German firms from 2005 to 2012, applies the exact same extended version of the CDM model, employs the same operationalization for the main variables, and even uses similar control variables. Table 11 reports the results of the resulting set of previous studies, Hypothesis 3 is not included because it has not been tested until now.

Table 11: Results from previous studies

	1st Stage: knowledge function			2nd Stage: productivity function		
	Product	Process	H1	Product	Process	H2
Study	(1)	(2)	(3)	(4)	(5)	(6)
Vasquez (2024)	0.094	-0.023	0.117	0.145	-0.891	1.036
Baumann & Kritikos (2016)	0.292	0.122	0.170	1.258	0.415	0.843
Griffith et al. (2006) A	0.44	0.303	0.137	0.060	0.069	-0.009
Griffith et al. (2006) B	0.273	0.260	0.013	-0.053	0.022	-0.075
Griffith et al. (2006) C	0.296	0.281	0.015	0.176	-0.038	0.214
Griffith et al. (2006) D	0.273	0.161	0.112	0.055	0.029	0.026
Hall et al. (2009)	0.250	0.193	0.057	0.193	0.597	-0.404
Mairesse & Robin (2008) A	0.530	0.300	0.23	0.570	1.120	-0.550
Mairesse & Robin (2008) B	0.550	0.420	0.130	1.090	0.310	0.780
Stojcic & Hashi (2014)	0.010	0.020	-0.01	-0.060	2.270	-2.33
Tevdovski et al. (2017)	0.820	0.243	0.577	0.326	1.145	-0.819

Notes: Column 1 and 2 report the marginal effect of predicted *R&D intensity* on the probability of introducing product innovation and process innovation, respectively. Column 3 reports the difference between the latter, the conclusion on Hypothesis 1 is based on such an estimate. Column 4 and 5 report the marginal effect of predicted probability of introducing product and process innovation on Productivity, respectively. Column 6 reports the difference between the latter, the conclusion on Hypothesis 2 is based on such an estimate. Vasquez (2024) refers to the present research, it observes firm in Germany from 2013-2017. Baumann & Kritikos (2016) observes firms in Germany from 2005-2012. Griffith et al. (2006) observes firms in France (A), Germany (B), Spain (C), and United Kingdom (D) from 1998-2000. Hall et al. (2009) observes firms in Italy from 1998-2004. Mairesse & Robin (2008) observes firms in countries of the European Union from 1998-2000 (A) and 2002-2004 (B). Stojcic & Hashi (2014) observes firms in countries of the European Union from 2004-2006. Tevdovski et al. (2017) observes firms in Germany during 2008.

Column 3 reports the difference between the marginal effect of *R&D intensity* on the product innovation and process innovation, evidence in this research suggests that knowledge returns to product innovation are higher than for process innovation. With the exception of Stojcic & Hashi (2014), who aggregates internal and external R&D, previous studies unanimously reach the same conclusion. Notably, the difference between knowledge returns found in this research is similar to that in Baumann & Kritikos (2016), Griffith et al. (2006), and Mairesse & Robin (2008).

Column 6 reports the difference between the marginal effect of product innovation and process innovation on *Productivity*, evidence in this research suggests that productivity returns from product innovation are higher than from process innovation. While Baumann & Kritikos (2016) reach to the same conclusion the rest of studies reach to either the opposite or conflicting conclusions. For instance, Griffith et al. (2006) and Tevdovski et al. (2017) finds that productivity returns from product innovation are lower for German firms. In the case of the former study, the authors apply independent probits in the 2nd stage of the extended CDM model, as for the latter study, the authors do not include the predicted probability of introducing both types of innovation in the 3rd stage. Furthermore, the large magnitude of the difference in productivity returns is noted. While evidence in this research suggests that product innovation increases *Productivity* more than introducing process innovation by 181.8%, evidence from other studies suggests a much more discrete and reasonable difference. It is argued that such an extreme finding is explained by the absence of control variables in the OLS estimation of the 3rd Stage of the extended CDM model. For instance, Baumann & Kritikos (2016) controls for *Size*, nevertheless, this research argues that such a variable is exogenous to innovation output because it was included in the estimation on the 1st stage.

In synthesis, previous evidence supports conclusions of this research about the difference in knowledge returns across innovation types, however, it is not always the case for conclusions about the difference in productivity returns. Since this research is the first to anal analyzed the impact of innovation output on economic risk, it is not possible to compare conclusions with previous studies.

6. Conclusion

Innovation is not random, capabilities and resources determine whether a firm becomes an innovator in a given economical context. Given technological risk and strategic dynamic, innovation develops under uncertainty. From a strategic perspective, innovation represents the decision to invest in knowledge to increase productivity through multiple ways. A firm may incorporate it into its own operations, sell it as an intangible asset, or use it to feed further knowledge.

The decision inevitably involves timing, size of investment, and choosing a type of innovation. Among the technological type, knowledge materializes in either a new product or a new process. This research argues that product innovation is more sensible to direct knowledge investments, namely R&D, because institutional and operational incentives are larger compared to process innovation which is rather more sensible to indirect acquisition of technology. Regarding their impact on the market, product innovation expands demand in the existing market or creates a new one, meanwhile, process innovation expands supply by reducing marginal costs. This research argues process innovation inferior because impact on productivity is ambiguous in the presence of different market conditions, meanwhile, product innovation certainly broadens revenue base. However, it is also argued that the radical nature of product innovation represents a higher risk in term of productivity returns.

This research is the first to compare knowledge and productivity returns from types of innovation, moreover, it analyzes a yet unexplored dimension of productivity. The empirical approach observes German firms from the manufacturing sector reported in MIP survey for the years 2013, 2015, and 2017. Besides its official and academic reputation, the MIP is a comprehensive source of information that contains both general and key innovative attributes of firms. Notably, this research observes relatively recent data compared to previous studies which mostly focus on the period before 2010. Following previous studies, an extended version of the CDM model is applied to test three hypotheses comparing the knowledge and productivity returns of product and process innovation. Apart from mitigating sources of endogeneity, the applied methodology resembles the idea that it is innovation output rather than innovation input which has an impact on economic performance of firms.

From the results of the estimation in the 1st Stage of the CDM model, evidence indicates that a potential selection bias is being corrected. Regarding knowledge returns, results from the 2nd stage give evidence that product innovation is more responsive to investment in R&D. Indeed, an increase in 1% of R&D intensity increases more the probability of introducing product compared to process innovation by 11.7 p.p., on average. This conclusion is robust to methodological choices and is widely consistent with previous studies. As for results in the 3rd stage, evidence confirms the hypothesis that productivity returns from product innovation are higher. Indeed, introducing product innovation increases revenue per employee more than introducing process innovation by 182 p.p., on average. While such a conclusion is partially robust, some previous studies reach opposite conclusions. Although not robust, evidence in this study suggests that product innovation is also riskier. Indeed, product innovation increases the probability of extreme revenues per employee more than process innovation by 35.7 p.p., on average. This is the first conclusion in literature regarding the impact of innovation of economic risk.

Certainly, this research acknowledges limitations related to the theoretical framework, data, and methodology. The channels by which product and process innovation impact productivity are clearly defined in literature, in general terms, while the former affects demand the latter affects supply. Under specific economic conditions (e.g., competition regime and differentiation), these channels have been formally modeled in literature (Bonanno & Haworth, 1996; Rosenkranz, 2003). It is argued that a simple but illustrative formal model would have integrated many mechanisms underlying the formulation of hypotheses. Instead, isolated theories (e.g. Product Life Cycle and Endogenous Growth) and multiple arguments are discussed in the theoretical framework.

Despite its reputation and extensive information, the MIP inherits the typical limitations of survey. Either a non-representative sample or a not random response pattern could potentially introduce bias to the estimations, besides, dishonesty or privacy concerns may lead to inaccurate answers. Moreover, the MIP deliberately drops firms from the survey for such privacy concerns (ZEW, 2023), as a result, it frustrates attempts to build a balanced panel although it is not impossible. This research conducts a robustness check for a balanced panel, overall conclusions do not change. There is a significant proportion of missing values for some variables, for instance, around 45% of observations do not contain information on *Physical capital*. Nevertheless, this research does not recognize this as a potential source of selection bias.

The dataset is a panel of German firms observed from 2013 to 2017, a panel estimation would have captured the intertemporal dynamics and deal better with endogeneity, indeed, the CDM model is by nature static in temporal terms (Crepon et al., 1998). For instance, reverse causality would not be a relevant issue if current *R&D intensity* estimates future innovation output. Peters (2007) intends to account for this concern by observing a balanced panel of German firms and applying a CDM model where stages are estimated in a chronological order, *R&D intensity* of 2000 estimates innovation output of 2001 and the latter estimates *Productivity* of 2002. The downside is that sample size shrinks to less than one thousand observations, besides, Griliches (1979) argues that expectations play a role in R&D investments. Furthermore, no econometric package is able to estimate a panel bivariate probit. Although *Size* is widely considered in previous studies for the exclusion condition in the Heckman selection model (1st Stage of the CDM model), it may not be ideal because *R&D intensity* would increase on firm size in the presence of returns to scale investments in knowledge. Nevertheless, from all the variables in the MIP survey *Size* is the only one for which there is empirical evidence that supports its use as a valid selection instrument (Cohen et al., 1987).

Another important criticism of the methodology refers to multiple measurement errors. Because knowledge accumulates over time, Griliches (1979) proposes to quantify it by the stock of R&D expenditures, nevertheless, this research and most of previous studies measures knowledge as the flow of R&D expenditure on each period. Crepon et al. (1998) originally estimated the R&D stock by adding observable R&D flows, they also suggest that using the flow does not change results significantly. Given the limited balance of the MIP dataset, following a similar methodology would reduce sample size drastically. Regarding innovation output, Mohnen & Hall (2013) note that using a binary variable does not account for the relevance of any type of innovation, for instance, a new product to the market might have a larger impact than a new product to the firm. Moreover, if a firm introduced multiple innovations, then a binary variable would not distinguish it from a firm that introduced just one (Hall, 2011). Some studies employ a more precise measure (Mairesse & Robin, 2017; Rammer 2023), Peters (2007) measures product innovation as sales from new products per employee and process innovation as cost reduction due to such an innovation per employee. Although this methodology might correct some measurements errors, few firms report this information in the MIP survey.

The conclusions of this research have implications about innovation strategy. If they have to choose, then firms should focus resources on introducing a new product rather than a new process. While conducting both types is always more convenient than focusing on one, the amount and combination of resources would not be affordable for every firm. Those committed to product innovation should not invest in R&D to create knowledge because it is a meaningless input, instead they may acquire novel technology. As for consumers, they can expect more diversity than a lower price for products offered by innovative firms. Governments can compensate for the risk of product innovation by reinforcing property rights and deregulating antitrust norms that deter product standardization.

Future research may expand the analysis of this research by employing a novel methodology that overcomes the many limitations discussed previously. A formal theoretical model would be a convenient starting point, although many conjectures could be inconclusive if strict, but necessary, assumptions are introduced. In the empirical stream, research should insist in the panel estimations because it is a practical wat to account for reverse causality. Regarding the analysis of economic risk, future research can easily explore this dimension of productivity in other geographies and time periods, also, alternative measures should be considered. Similarly, previous studies can expand their analysis by comparing innovation types without major efforts, its just a matter of conducting a test on the difference of marginal effects. Research must find or improve the motivation of a variable to be employed for the exclusion condition in the 1st Stage of the CDM model, as discussed before, *Size* was partly considered because there was no other convincing alternative. Perhaps a clearer comparison could be made between technological and non-technological innovation, the use of technology would be the obvious mechanism, but other arguments may be also proposed by future research. Modern tools may overcome many measurement errors, instead of using binary variables firms may be classified with Machine Learning to compare types of innovative firms rather than innovation types itself.

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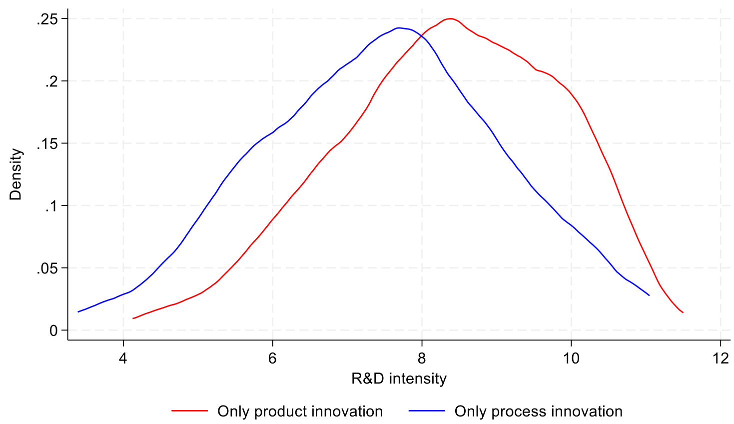
Appendices

Appendix A

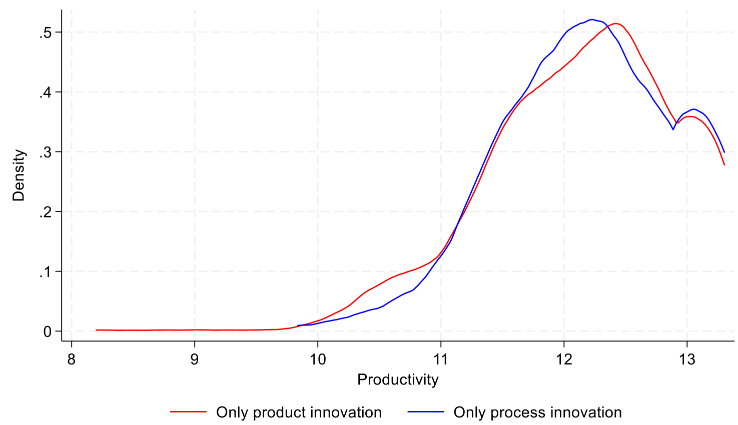
Figure A1: Density of *R&D intensity* by selected categories of *Innovation*



Notes: The selected categories are "Only product innovation" and Only process innovation". For simplicity, the categories "Only product innovation" and Only process innovation" are referred as "Product" and "Process", respectively.

Appendix B

Figure A2: Distribution of *Productivity* by selected categories of *Innovation*



Notes: The selected categories are “Only product innovation” and Only process innovation”. For simplicity, the categories “Only product innovation” and Only process innovation” are referred as “Product” and “Process”, respectively.

Appendix C

Table A1: Descriptive statistics by not selected categories of *Innovation*

	None		Both		Total	
Variable	N	Mean	N	Mean	N	Mean
R&D intensity	297	7.744	1,233	8.405	2,656	8.231
Product	3,851	0	1,981	1	8,551	.45
Process	3,851	0	1,981	1	8,551	.331
Productivity	3,822	12.085	1,979	12.306	8,517	12.178
Risk	3,822	.236	1,979	.172	8,517	.203
Structure	3,839	.244	1,969	.438	8,509	.316
Competition	3,450	.511	1,892	.439	7,950	.484
Internationalization	3,271	.503	1,705	.829	7,347	.65
Physical capital	2,091	.162	1,219	.133	4,855	.138
Exports	3,271	.136	1,705	.309	7,347	.209
Capital intensity	2,789	.043	1,519	.055	6,332	.046
Training	2,660	.006	1,456	.011	6,029	.008
IC	3,016	.004	1,572	.007	6,727	.005
Cooperation	3,851	.036	1,981	.415	8,551	.188
Public support	3,851	.033	1,981	.351	8,551	.166
Appropriability	3,515	.04	1,769	.265	7,655	.143
Source customers	3,083	.11	1,478	.719	6,527	.396
Source suppliers	3,077	.089	1,470	.479	6,510	.27
Source competitors	3,083	.102	1,477	.54	6,525	.326
Source academy	3,081	.049	1,477	.362	6,509	.179
Hamper	2,354	.477	1,439	.597	5,694	.537

Notes: The sample is split into four sub-samples according to four categories of variable *Innovation*, only subsamples corresponding to the not selected categories are reported in this table. The selected categories are “Only product innovation” and Only process innovation”.

Appendix D

Table A2: Distribution of *Year* by categories of *Innovation*

	Innovation				
Year	None	Product	Process	Both	Total
2013	1,439	681	295	761	3,176
%	45.31	21.44	9.29	23.96	100.00
2015	1,309	606	231	611	2,757
%	47.48	21.98	8.38	22.16	100.00
2017	1,103	584	322	609	2,618
%	42.13	22.31	12.30	23.26	100.00
Total	3,851	1,871	848	1,981	8,551
%	45.04	21.88	9.92	23.17	100.00

Notes: Percentages are computed for each row. For simplicity, the categories “Only product innovation” and Only process innovation” are referred as “Product” and “Process”, respectively.

Appendix E

Table A3: Distribution of *Age* by categories of *Innovation*

Age	Innovation				Total
	None	Only Product	Only Process	Both	
After 2010	304	159	63	137	663
%	45.85	23.98	9.50	20.66	100.00
From 2000 to 2009	671	330	170	393	1,564
%	42.90	21.10	10.87	25.13	100.00
From 1990 to 1999	1,215	592	250	625	2,682
%	45.30	22.07	9.32	23.30	100.00
Before 1990	1,657	788	365	824	3,634
%	45.60	21.68	10.04	22.67	100.00
Total	3,847	1,869	848	1,979	8,543
%	45.03	21.88	9.93	23.17	100.00

Notes: Percentages are computed for each row. For simplicity, the categories "Only product innovation" and Only process innovation" are referred as "Product" and "Process", respectively.

Appendix F

Table A4: Distribution of *Size* by categories of *Innovation*

	Innovation				
Size	None	Product	Process	Both	Total
Micro	1,880	665	271	473	3,289
%	57.16	20.22	8.24	14.38	100.00
Small	775	391	160	354	1,680
%	46.13	23.27	9.52	21.07	100.00
Medium	504	322	155	320	1,301
%	38.74	24.75	11.91	24.60	100.00
Large	422	282	143	377	1,224
%	34.48	23.04	11.68	30.80	100.00
Corporate	246	209	118	457	1,030
%	23.88	20.29	11.46	44.37	100.00
Total	3,827	1,869	847	1,981	8,524
%	44.90	21.93	9.94	23.24	100.00

Notes: Percentages are computed for each row. Category "Micro" of *Size* refers to firms with less than 20 full-time employees, "Small" to firms with between 20 and 50, "Medium" to firm with between 50 and 100, "Large" for firms with between 100 and 250, and "Corporate" to firms with more than 250. For simplicity, the categories "Only product innovation" and Only process innovation" are referred as "Product" and "Process", respectively.

Appendix G

Table A5: Distribution of *Sector* by categories of *Innovation*

Sector	Innovation: None	Innovation: Only product	Innovation: Only process	Innovation: Both	Total
Mining	475	63	83	70	691
%	68.74	9.12	12.01	10.13	100.00
Food/Tobacco	449	168	84	128	829
%	54.16	20.27	10.13	15.44	100.00
Textile	305	162	46	107	620
%	49.19	26.13	7.42	17.26	100.00
Wood/Paper	281	82	69	100	532
%	52.82	15.41	12.97	18.80	100.00
Chemical	171	163	34	196	564
%	30.32	28.90	6.03	34.75	100.00
Plastics	214	93	64	131	502
%	42.63	18.53	12.75	26.10	100.00
Glass/Ceramics	210	65	38	75	388
%	54.12	16.75	9.79	19.33	100.00
Metals	645	167	176	232	1,220
%	52.87	13.69	14.43	19.02	100.00
Electrical equipment	271	337	68	384	1,060
%	25.57	31.79	6.42	36.23	100.00
Machinery	173	225	43	256	697
%	24.82	32.28	6.17	36.73	100.00
Retail/Automobile	131	111	48	118	408
%	32.11	27.21	11.76	28.92	100.00
Other	526	235	95	184	1,040
%	50.58	22.60	9.13	17.69	100.00
Total	3,851	1,871	848	1,981	8,551
%	45.04	21.88	9.92	23.17	100.00

Notes: Percentages are computed for each row. *Sector* category “Others” stands for sectors Furniture, Toys, Medicine, Technology and Maintenance. For simplicity, the categories “Only product innovation” and Only process innovation” are referred as “Product” and “Process”, respectively.

Appendix H

Table A6: Distribution of *Human* capital by categories of *Innovation*

	Innovation				
Human capital	None	Product	Process	Both	Total
x=0	1,164	252	144	149	1,709
%	68.11	14.75	8.43	8.72	100.00
0<x<5%	469	218	137	201	1,025
%	45.76	21.27	13.37	19.61	100.00
5%<=x<10%	563	267	165	354	1,349
%	41.73	19.79	12.23	26.24	100.00
10%<=x<15%	479	291	137	330	1,237
%	38.72	23.52	11.08	26.68	100.00
15%<=x<20%	189	152	48	177	566
%	33.39	26.86	8.48	31.27	100.00
20%<=x<30%	316	202	62	248	828
%	38.16	24.40	7.49	29.95	100.00
30%<=x<50%	179	185	50	201	615
%	29.11	30.08	8.13	32.68	100.00
50%<=x<75%	77	114	19	102	312
%	24.68	36.54	6.09	32.69	100.00
75%<=x<=100%	59	58	10	41	168
%	35.12	34.52	5.95	24.40	100.00
Total	3,495	1,739	772	1,803	7,809
%	44.76	22.27	9.89	23.09	100.00

Notes: Percentages are computed for each row. For simplicity, the categories “Only product innovation” and Only process innovation” are referred as “Product” and “Process”, respectively.

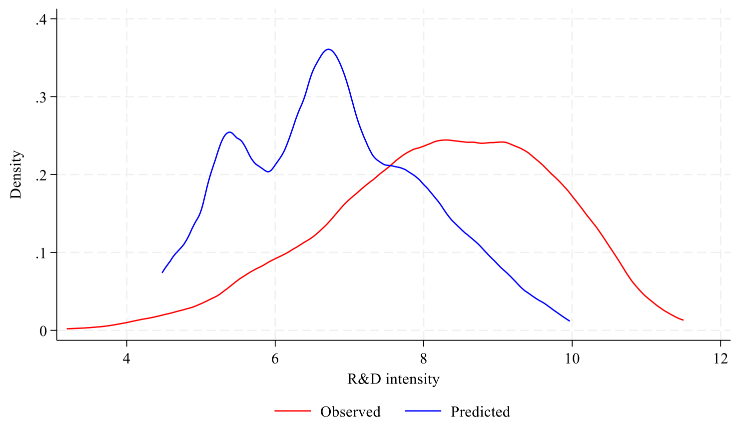
Appendix I

Table A7: Pairwise correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) R&D intensity	1.0																				
(2) Product	0.3	1.0																			
(3) Process	0.1	0.1	1.0																		
(4) Productivity	0.2	-0.0	0.1	1.0																	
(5) Risk	-0.0	0.0	0.0	-0.1	1.0																
(6) Structure	0.1	-0.0	0.1	0.4	0.0	1.0															
(7) Competition	-0.0	-0.0	-0.0	-0.1	0.0	-0.1	1.0														
(8) Internationalization	0.1	0.1	0.0	0.2	-0.1	0.1	-0.0	1.0													
(9) Physical capital	0.1	-0.0	0.1	0.2	0.2	0.1	0.0	-0.1	1.0												
(10) Exports	0.2	0.1	0.0	0.3	0.0	0.3	-0.1	0.4	0.0	1.0											
(11) Capital intensity	0.0	0.0	0.1	-0.1	0.1	0.0	0.0	-0.1	0.4	-0.1	1.0										
(12) Training	0.2	0.1	0.1	-0.0	0.0	-0.1	0.0	-0.1	0.1	-0.1	0.1	1.0									
(13) ICT	0.2	0.0	0.0	-0.1	0.0	-0.0	0.0	0.0	0.0	0.1	0.2	0.1	1.0								
(14) Cooperation	0.2	0.1	0.1	-0.0	0.1	0.1	-0.1	0.0	0.0	0.1	0.0	0.0	0.0	1.0							
(15) Public support	0.3	0.1	0.0	-0.1	-0.0	-0.1	-0.1	0.1	-0.0	0.0	0.0	0.1	0.0	0.5	1.0						
(16) Appropriability	-0.1	0.0	-0.0	-0.3	-0.0	0.0	-0.0	0.1	-0.1	0.1	-0.0	0.0	-0.0	0.1	0.0	1.0					
(17) Source customers	0.1	0.2	0.1	-0.0	0.1	0.1	-0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	-0.0	0.0	1.0				
(18) Source suppliers	-0.1	0.0	0.1	0.1	0.0	0.1	0.0	-0.0	-0.1	0.1	-0.0	0.0	0.0	0.0	-0.1	0.0	0.1	1.0			
(19) Source competitors	0.1	0.0	0.0	0.1	-0.1	0.0	0.1	0.1	-0.0	0.1	-0.0	0.0	-0.0	-0.1	-0.1	0.0	0.2	0.2	1.0		
(20) Source academy	0.2	0.0	0.0	0.1	0.0	0.1	-0.0	0.1	0.0	0.1	-0.0	0.0	-0.0	0.4	0.3	0.0	-0.0	0.0	0.1	1.0	
(21) Hamper	-0.0	-0.0	0.0	-0.1	-0.0	-0.1	0.1	-0.1	0.0	-0.1	0.0	0.1	0.1	-0.0	0.0	-0.0	0.0	0.1	0.1	0.0	1.0

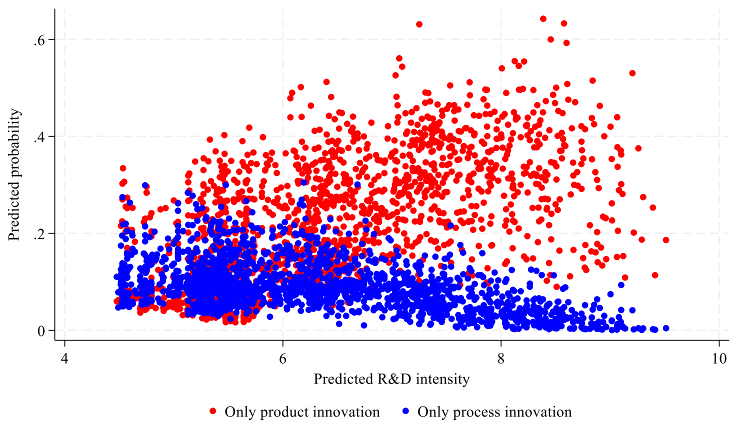
Appendix J

Figure A3: Distribution of observed and predicted *R&D intensity*



Appendix K

Figure A4: Predicted *Product* and *Process* over predicted *R&D intensity*



Notes: Only firms observed in 2013 are plotted.

Appendix L

Equation 5 models the introduction of combinations of innovation output by firms.

$$I_{ji} = \xi_{ji} r_i^{\mathrm{p}} + Z_i \Theta_{\mathrm{j}} + \epsilon_{ji} \tag{5}$$

Where I_{ji} is vector of j binary variables denoting a categorical variable which indicates the combination of innovation types introduced by the firm i (*Innovation*), the corresponding categories are four: (1) None, (2) Only product innovation, (3) Only process innovation, and (4) Both. Given the nature of the dependent variable, a Multinomial Logit mode estimates Equation 5 as in Cabagnols & Le Bas (2002). The authors extend the original CDM model by distinguishing the effect of *R&D intensity* on each of the possible combination of innovation output. An advantage of this alternative over the Bivariate Probit is that it isolates the impact of innovation input of the probability of introducing both types of innovation. As a result, it is possible to compare how product or process innovation alone respond to *R&D intensity*. Similarly to the Bivariate Probit, this estimation al predicts the probability of every innovation combination, however, it does not account for the correlation between the j error terms ϵ.

As an alternative, Hypothesis 1 is tested by conducting a one-tail significance t-test on the following expression

$$M.E.(\xi_2) - M.E.(\xi_3) = 0$$

Where $M.E.(\xi_2)$ and $M.E.(\xi_3)$ denote the marginal effect of *R&D intensity* on the likelihood of introducing only product and only process innovation, respectively. A positive and significant estimate would confirm that knowledge returns from R&D are higher for product compared to process innovation.

Appendix M

Table A8: Panel pattern of the sample

			Pattern		
Frequency	% frequency	Cumulative	2013	2015	2017
1,467	26.06	26.06	X		
1,032	18.33	44.4			X
958	17.02	61.41		X	
750	13.32	74.74	X	X	X
586	10.41	85.15	X	X	
463	8.23	93.37		X	X
373	6.63	100	X		X
5,629	100				

Notes: There are 5,629 different firms in the sample. Column "Cumulative" refers to the cumulative percentage frequency.