Gonchar, Ksenia; Kristalova, Maria

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How innovation affects performance

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by

Ksenia Gonchar
Maria Kristalova

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How innovation affects performance[1]

Ksenia Gonchar+

Maria Kristalova++

Abstract

This paper studies how innovation strategies of Russian manufacturing firms affect various features of firm performance. A multi stage model is used, which relates the firm's decision to undertake R&D to its innovation output, technical efficiency, labor productivity, and growth. We also include imports into the knowledge production function, because catching up economies may adopt technologies embodied in imported hardware. Additionally, we link productivity and innovation output to survival. We find that both types of knowledge input – R&D and imports – strongly determine innovation. Innovations yield the strongest performance return in the case of catching up to technological frontier. Product innovation is more beneficial than process innovation in all performance features except for labor productivity. However, higher efficiency does not improve the growth rates or survival time of manufacturing firms. Taken together, these results show that innovation is not uniformly rewarded across all features of firm performance.

JEL classification: C30, D24, O30

Key words: innovation; productivity, growth, survival, Russia

+ Contact: kgonchar@hse.ru, National Research University Higher School of Economics, Moscow, Russia.

++ Contact: maria.kristalova@uni-jena.de, Bremen University and Friedrich-Schiller-University Jena, Jena, Germany.

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1. Introduction[2]

Despite sound theoretical claims that technological changes determine growth and productivity differences across firms, these expectations are not always supported by empirical data in emerging countries. Firms in Russia could raise output and productivity on the basis of little investment or innovation by drawing on under-employed stocks of capital and labour and increased private consumption (Ahrend 2004). The ability of firms to receive a return from innovations is reduced by a low degree of competition and a weak market selection mechanism, which allows inefficient firms to remain in the market and even grow. For example, (Bogetić and Olusi 2013) establish that Russian manufacturing firms' survival is weakly correlated to productivity (TFP). They conclude that managerial incentives in incumbent firms may not strongly favour the productivity-innovation link when competition is weak. In general, factors which affect the technological advance and connection between firm innovation and the performance in transition countries are still poorly understood. The empirical literature frequently identifies financial constraints as the main barrier restraining the ability of firms to catch up to the technological frontier (Hall and Lerner 2009; Gorodnichenko and Schnitzer 2013). The innovation-performance link in latecomer countries, as compared to frontier economies, may be reduced by a low market value of the novel products and resulting smaller profits from innovation (Hu, Kang, and Wu 2017). Additionally, the more incremental and less radical nature of innovation renders a conventional measurement methodology inappropriately designed to quantify the innovation effort and its performance effect in this group of countries (Cirera and Muzi 2016).

This paper attempts to contribute to the understanding of the relation between innovation and firm performance in transition economies by analysing the innovation strategies of Russian manufacturing firms. The main research question is which performance characteristic -productivity gains, output growth, or survival - is rewarded by innovation in the

[2] The authors wish to acknowledge the valuable assistance with the preparation of the data by Olga Uvarova and insightful comments by Professor Jutta Guenther, Professor Torben Klarl, and participants of the ierp seminar at the University of Bremen

presence of relatively low competition, high uncertainties, and a weak market selection mechanism? To what extent is performance influenced by various forms of innovation? How does the effect differ across different sources of knowledge inputs? How do size, location, and market selection intervene in the innovation-performance relation?

The Russian manufacturing industry is a motivating empirical setting for the analysis of the performance-innovation link in transition economies. It is large and structurally sophisticated: the manufacturing value added accounted for 12% of GDP in 2016, which is comparable to Brazil (10.3%) and Poland (18.1%), and half the level of the Czech Republic (24.4%) and China (28.8%) (World Development Indicators 2018). The industry went through several boom and bust cycles in recent years in response to transition and cyclical dynamics. It contracted severely in 2009 during the world economic crisis and again in 2015, when the geopolitical situation, the fall of commodity prices, sanctions, and a national currency devaluation caused a major downturn. In total, the Russian manufacturing industry lost more than two million jobs between 2002 and 2015 (Rosstat 2018).

This paper builds on the previous literature treating the innovation-performance link and is mostly inspired by the Schumpeterian and evolutionary school of thought and contributes to this literature by introducing four important novelties. Firstly, by using a unique dataset comprised of matched survey and registry data to compare the innovation impact on three performance indicators – productivity, growth, and survival. The modified Crépon, Duguet, and Mairesse (Crépon, Duguet, and Mairesse 1998) — henceforth CDM — model is estimated for the cross-section and panel data. Post-innovation performance is analyzed for the next three years after the survey was conducted. Studies of innovation effects on various performance characteristics rarely overlap. Therefore, this paper provides new insights into the innovation-performance literature. Secondly, innovation input is not limited to R&D expenditures but is complemented by knowledge input generated by imports of machines and equipment – the most typical source of technologies for the firms in emerging economies. Thirdly, we distinguish effects of innovation on labor

productivity and on technical efficiency (TE) in terms of their distance to the production frontier, thus emphasizing nuances of technological and cost competitiveness. Finally, by using the Cox proportional hazard model, we investigate how innovation, growth, and productivity advantages translate into a longer survival time and thus expand the CDM concept into the most critical performance characteristic of the firm.

The findings show the complexity of the innovation-performance link: in general, innovations are rewarded, but not across all components of overall performance and not across all types of innovation. The highest return is found for catching up to the technological frontier: product innovation is a strong contributor to the shortening of the distance to the most efficient firm in 4-digit sector and is furthermore beneficial for growth and survival. Process innovation contributes mostly to labour productivity and growth. In turn, achieved technical efficiency results in greater innovation output, whereupon technological superiority decides further innovation. Innovation improves the growth rate and increases the achieved survival time, though both growth and survival are mostly dependent on the overall evolution of the industry. Contrary to expectation, more efficient firms do not survive longer and, as a consequence, the efficiency of resource allocation and market selection mechanisms may be questioned.

The implication of these results is that in spite of the specificity of the Russian market structure and institutional setting, our findings are consistent with the predictions of the evolutionary literature concerning the innovation-performance relationship. The departure from the theory relates to the low correlation between productivity advantages and survival and growth.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data and key variables used in analysis. Section 4 presents the empirical strategy. Section 5 describes the findings, Section 6 concludes.

2. Theory and findings of the empirical literature

We build our research on the conceptual framework of the Schumpeterian and evolutionary approach to innovation activity as a main engine of change. It establishes that technological advances develop as an evolutionary process in which innovations shape all of the three dimensions of a firm's performance we seek to study in this paper: productivity, growth rates and survival behavior (Dosi 1988; Klepper and Thompson 2006; Nelson and Winter 1982b; Pavitt 1999). This framework is particularly relevant for the emerging economies that often adopt productive technologies employed before in high-income countries.

Firms are viewed as complex dynamic organizations that explore the technological frontier as they learn from new technologies. Technical change within firms is related to technological opportunities in the industry and to the environment with a selection mechanism, applying when innovation benefits are dependent on product demand and factor supply conditions, as well as on the behavior of other firms in the sector. According to this perspective, if productivity depends on technological opportunities within sectors, then R&D and innovations in some sectors are more productive than in others. Additionally, differences in the selection environment lead to various speeds of diffusion of technologies and new products.

The firm learns not only as a result of R&D. It often seeks to complement or balance inventions with an application of existing knowledge from external sources (Dosi 1988). Imports of machines and equipment may therefore be viewed as a carrier of specific productive knowledge, provided that importing firms can learn from the R&D investments made earlier by their trade partners (Coe and Helpman 1995).

This leads us to the first hypothesis:

H1. Productivity evolution is determined by the firms' innovation decisions, which in turn depend on knowledge input provided by R&D and imports.

The next important prediction of evolutionary economics refers to the role of achieved productivity and profit as mechanisms stimulating the

search for novel products and the departure from existing routines (Hall and Jones 1999; Winter 1975; Witt 1996). This sequence of evolutionary knowledge creation, learning, and a further application of knowledge determines the intensity and efficiency of innovation. Thus, we hypothesize the bidirectional causality between innovation and productivity:

H2. Not only does innovation stimulate productivity, but innovation may also be driven by economic returns from previous innovation. Therefore, former advantages in technical efficiency strengthen further innovation.

Within the same theoretical framework of evolutionary economics, gaps in productivity across firms as an outcome of the search and learning process consequently result in differences in growth rates among firms (Aghion and Howitt 1992; Nelson and Winter 1982a). Innovation should result in economic growth due to the greater variety of products, their superior quality, the unique nature of new technologies and products, and cost advantages. However, the outcome is not guaranteed and is conditioned by various factors (Griliches 1998; Hall and Jones 1999). The positive effects may be curtailed by liquidity problems, inefficient allocation, and other difficulties the firm faces. Innovating firms may fail to obtain an economic return from innovation, leading them to shrink and die even though they are innovation leaders. They may, for example, not have sufficient capacities and complementary assets, or a new product might not meet sufficient demand (Teece 1986). The recent model by (Hommes and Zeppini 2014) shows the role of demand in technological change: when the demand is elastic, technological progress leads to an ever-increasing fraction of innovators. With inelastic demand, technological progress is characterised by fewer and fewer innovators instead.

The extended Nelson and Winter model (Winter 1984) introduces entry dynamics as a pattern of the broader evolution of the industry, outlining a situation in which the incumbents are challenged by the new firms which enter with the new technologies, thus forcing the mature firms to innovate or to contract. This expectation is complemented by the notion

of the industry life cycle (Klepper and Sleeper 2005) with the various backgrounds of the entrants in different industries.

Hence, our hypothesis for an innovation-growth link may be formulated as follows:

H3. Innovation and related productivity gains are associated with growth conditional on firm's survival and positive industry dynamics.

In turn, the survival perspectives of the firms depend on how they transform advantages in productivity, profitability, and scale economies into the better survival chances (Aghion, Howitt, and García-Peñalosa 1998; Audretsch 1995; Griliches 1979). Several factors may cause a variation in the probability of survival, depending on innovations. First, the market selection mechanism matters: a turnover of firms occurs when competitive pressure induces the exit of inefficient firms (Hopenhayn 1992), therefore if the selection mechanism is inefficient, the productivity-survival link may be disrupted. Second, the survival-innovation link in mature industries has certain specificities. As (Agarwal and Gort 2002) write, a mature market is characterized by fewer technological opportunities, a shift of innovation to minor product refreshments and cost reduction, and from pure innovation to imitation. All this leads to more intense competition and lower rates of survival. Moreover, technologically intense industries may be associated with higher hazard rates because of the speedy obsolescence of the initial endowment in such industries. Firm age and economies of scale are other important factors: (Jensen, Webster, and Buddelmeyer 2008) study the innovation-survival link for young and mature firms and report that young firms are more prone to an early death in general, but they more likely succeed in risky and innovative industries than do mature firms.

From this follows the fourth hypothesis:

H4. Innovations and higher productivity lead to a higher chance of survival, especially for small firms, which are usually more likely to die.

The empirical literature reports various outcomes of innovation efforts regarding the various performance characteristics, types of innovation, and level of development of the host economy. With respect to

the innovation-productivity link, the existing literature generally documents large and persistent productivity differences among producers and traces these differences to innovation efforts (Syverson 2011). A survey of the productivity-innovation literature (Hall 2011) shows that most research at the microlevel finds positive effects of product innovation on productivity, though the elasticities for developed countries are considerably higher than for less developed countries. The effects in the manufacturing industry are found to be higher than in services, and in the low technology sectors they are lower than in mid- and high technology. Concerning imports as a source of knowledge for innovation, the literature is quite conclusive: imports contribute to innovation and performance (see (Wagner 2012) for a literature review). The mechanisms behind import spillovers include the improvement of technologies, the quality of products (Damijan, Konings, and Polanec 2014), and the development of new routines which are adopted through imitation and reverse engineering (Goldberg et al. 2010).

The estimation results for process innovation and productivity are less consistent, the effects found being negative, zero, and rarely positive. This may be explained by the different mechanisms behind the effects of product and process innovations on productivity and by the difficulties of measuring new production technology in an appropriate manner (Mohnen and Hall 2013; Crespi and Pianta 2008). In general, product innovations increase productivity by increasing output, entering the new markets, and increasing demand, while process innovations reduce costs and lead to higher capital intensity, which contributes to cost advantages. Both ways to accumulate dynamic capabilities entail significant costs and risks, which can be disruptive in a weak economy. Therefore, the expected benefits of innovation on performance in weaker economies are lower compared to more developed countries

Regarding the innovation-growth perspective, there remains a degree of ambiguity in the empirical literature. Some studies conclude that innovation matters for firm output growth, some however do not find a strong link between innovation and sales growth (for the extensive literature survey see (Coad 2009)). The ambiguous effects are explained

by the large time lags between the time of invention and introduction of the new product, as well as by the combination of cost and risk involved (Coad and Rao 2008). Uncertainties also force firms to delay risky investment decision needed to bring innovative products to the market (Bloom and van Reenen 2002). Additionally, markets often fail to serve as effective selectors for delivering the rewards of economic growth according to a firm's productivity advantage (Audretsch, Segarra, and Teruel 2014). A low persistence of growth rates over time may also present difficulties for finding the effects of innovation on firm growth (Audretsch, Coad, and Segarra 2014).

Recent empirical studies claim that innovation interacts with third factors when it determines the growth effects. Therefore, the link is positive only for some firm groups and in general there appear to be limits to this positive relationship. (Coad and Rao 2008), for example, report that R&D and patents increase the growth rates of fast-growing firms, while for others the effect may be zero or negative. (Grillitsch, Schubert, and Srholec 2019) show that only broader sources of knowledge and their combinations, as opposed to just R&D, drive innovation and firm growth. They also find evidence of a non-linear link between knowledge and growth according to which, beyond certain thresholds, an increase of the knowledge base results in decreasing firm growth. Conditions for a positive innovation-growth link may include types of innovation activities under which product innovation rather than process contributes to growth (Santi and Santoleri 2017). Furthermore, the continuality of the innovation process may also matter (Triguero, Córcoles, and Cuerva 2014; Deschryvere 2014). A favorable location and geographical knowledge spillovers may condition pertaining positive effects (Audretsch and Lehmann 2005). In turn, (Demirel and Mazzucato 2012) report that restrictions of an effective innovation-growth link are incurred due to insufficient economies of scale and a lack of persistence in patenting.

A weak selection mechanism conditioned by weak competition is often quoted as a serious barrier to firm turnover based on efficiency advantages. For example, (Tybout 2000) suggests a higher patience of markets toward inefficient firms in developing economies, where large

incumbents may be protected from death irrespective of their innovation and productivity. (Ugur, Trushin, and Solomon 2016) report on UK data that R&D active firms survive longer in more concentrated industries. However, despite the ambiguity of protection policy in emerging economies, large protected incumbents often carry out significant innovation efforts, like Petrobras and Embraer in Brazil, Temasek in Singapore, or SANY Group in China (OECD, 2015).

Upon the whole, empirical studies on data relating to transition economies do not indicate that the innovation-survival link follows a special pattern in this group of countries. For example, in China, where the government largely protects state-owned firms, the studies show a positive relationship between survival and productivity (Audretsch et al. 2016; Yu et al. 2015). Some studies suggest an inverted U-shaped relationship (see (Zhang and Mohnen 2013) for the link between R&D intensity and survival). A comparable relationship is demonstrated for Chile (Fernandes and Paunov 2015), where product innovation is shown to be beneficial for the survival of plants, though the effect is confirmed only for multi-product plants and relatively low levels of risks.

Previous research on the Russian data generally finds some positive performance effects of innovation. Regarding the innovation-productivity link, (Roud 2018) uses the CDM modelling on the data of the national innovation survey. He reports that innovation output, measured as innovation sales per employee, positively influences labor productivity. Imports as an input into innovation decisions are studied on survey manufacturing data by (Gonchar and Kuznetsov 2018): the paper reports beneficial effects of importing on firm innovation between 2005 and 2009 and a higher impact of imports on product innovation rather than on process innovation. Concerning growth effects, (Chadee and Roxas 2013), using the World Bank survey data for 2009 within the structural equation modelling, report a positive influence of innovation on sales growth, conditional on the quality of the institutional environment. (Golikova et al. 2017) describe how Russian manufacturing firms which invested in tangible assets prior to the 2008-2009 crisis have been more likely to demonstrate higher growth rates during the recovery and the

immediate post-crisis period. Finally, (González, Iacovone, and Subhash 2013), using the United Nations Industrial Development Organization (UNIDO) dataset, study the productivity-survival link and conclude that in general more productive manufacturing firms are less likely to exit than less productive ones, though this finding does not hold for sectors where competition is less intense and unproductive firms are less likely to exit. Furthermore, improved productivity improves companies' survival chances mostly during economic surges rather than during slumps. To the best of our knowledge we are not aware of studies that use TE measures to analyze the relationship between innovation and productivity in Russia and compare various performance outcomes of innovation efforts.

3. Data and descriptives

3.1. Data sources

The data we use for estimation come from a manufacturing firms' survey of about 2,000 manufacturing plants of all sizes, carried out by the National Research University Higher School of Economics in 2014 in the framework of face-to-face interviews[3]. The resulting main sample includes firms randomly stratified by manufacturing sectors and size groups of enterprises, but not by subnational regions. The sample is somewhat skewed towards larger firms; therefore, where possible, we weight data to bring our sample close to the structure of the general population of manufacturing firms. For the weights we use the inverse of the observations' sampling probabilities across 2-digit sectors and size groups of firms.

We merge survey-related establishment level indicators to later performance data from the Ruslana dataset collected by Bureau van Dijk. Additionally, we use sector-specific data, calculated by the authors using the manufacturing industry population data as reported by Ruslana. This allows us to take into consideration that, when the innovation decision is made, this may affect revenue subject to a time lag and therefore avoids the problem of simultaneity of firm decisions concerning innovation,

[3] The dataset, questionnaire and methodology of sampling and data collection may be found under https://iims.hse.ru/rusfirms

investments, and organization, thus reducing the endogeneity risk. All performance data is deflated with the use of a 4-digit sectoral price index.

While the survey is conducted at the plant level, we do not distinguish between plants and firms in this study. To capture the specificity of the ownership pattern in the Russian manufacturing industry we control all estimations for the measurement that distinguishes between independent and dependent plants (Holding dummy).

The strength of this study lies in the combination of two independent data sources. This allows us to measure innovation directly, based on the self-perception of company managers, while accounting data for the post- and pre-survey period enable us to assess the impact of lagged measurements of firm organization and behaviour on later performance. In addition, combining survey and accounting data reduces common method bias, which is a usual occurrence for survey statistics.

3.2. Dependent variables.

This paper seeks to explain three performance measurements that are expected to be impacted by innovation decisions. They are the productivity, the growth rate, and firm survival.

Productivity, generally understood as efficiency in production, is measured in two ways – either as total factor productivity (technical efficiency, TE) computed by means of stochastic frontier analysis, or as labor productivity (real operational turnover per worker). TE takes account of the firm's efficiency and shifts in the sectoral technological frontier. Because we lose a lot of observations with TE, additionally we use simple labor productivity as a measure of efficiency: this indicator is easy to understand and to measure, though it does not reflect the intensity of use of factors other than labor input factors. Our data shows a large within sector's gap in TE estimates among manufacturing plants in the year when the survey was conducted: the average firm in the 90th percentile of TE distribution is 1.6 times closer to the technological frontier than the average firm in the 10th percentile.

The second dependent variable is the growth rate measured as annual real growth of operational revenue, deflated with the use of 4-digit sectoral prices indexes (2010 being the base year).

As it relates to survival, our dependent variable is the number of years between 1991 (the year when the market reforms started) and the failure event by 2018. A plant is defined as exiting when it is not operational in year *t* as compared to the year *t-1* and has either permanently closed, remains in the process of liquidation, or was acquired by another firm. In our data, the share of exits falls monotonically with the firm size: in the group of companies with 10-19 employees 42.7% of firms exited the market whereas the percentage stood at only 2.3% for plants with more than 500 workers. Companies face different operational risks depending on sector affiliation: the highest mortality rate is observed in the timber and food-processing sector (21.7% and 20.2% of firms exited respectively), the lowest being found among firms which belong to the transportation equipment industry (about 2%).

<< Table 1 about here >>

<< Figure 1 about here >>

3.3. Independent variables

We do not observe the full history of surveyed firms before and after the survey was conducted and rely on several self-reported indicators of R&D, innovation, firm organization, and ownership. R&D as innovation input is measured by two indicators. First, by the dummy constructed by asking if the firm performed R&D three years prior to the survey. Second, R&D intensity is calculated from the answers to the question about the mean share of R&D expenditures in sales within the three years prior to the survey and is defined as the logged value of R&D expenditures per employee. The indicator of R&D intensity is used to explain innovation output in a knowledge production framework and to additionally test for H.4 when R&D - survival effects are studied. In our data, the mean value of R&D of a typical manufacturing firm accounts for about RuR 19

thousand per employee in 2014 – approximately an average monthly wage in manufacturing.

Additionally, our econometric strategy takes into account the specificity of innovation processes in transition economies, seeing as relying on the R&D input into the knowledge function may underestimate the innovation effort especially in smaller firms in traditional sectors. We assume that the plant receives knowledge either through R&D or by learning from technologies embodied in imported machines and equipment. Import participation is measured as a logged value of imports per worker and is constructed from the questions about the share of imports of machinery and equipment in fixed assets.

In our data, some differences in R&D and import participation are observed: 16.9% of plants report R&D expenditures and 23.9% import hardware. Overall 32.5% of the sampled plants engage in at least one of the learning activities, which we expect to serve as an input into innovation.

We measure innovations following the procedure applied in most innovation surveys by asking if the plant introduced a new or significantly improved product or production technology during the past three years prior to the survey (that is between 2011 and 2014). Thus, we get the dummy for product innovators (48.2% of observations) and a dummy for process innovators (33.3% of observations).

This measurement is extensively used in survey-based empirical literature, albeit for some important drawbacks – for instance, its inability to fix the exact timing of innovation and to correct for size, seeing as larger firms obviously have more product lines and are thus more likely to be counted as product innovators (see the survey by (Mairesse and Mohnen 2010)). Therefore, to measure product innovations, we use the responses to the question about the mean share of the plant's sales due to new products within the three years prior to the survey. From these responses we construct our measurement of innovation output for product innovations – the real sales of novel products per worker. This indicator is often regarded as a relatively accurate measure because it highlights the

persistence of successful product innovations, thus profiting from the fact that most firms track their sales by type of product.

We use a comparable approach to capture process innovations because of the above-mentioned fuzziness of innovation dummies. In the survey, we have the question about the age structure of machines and equipment. We assume that the share of machines and equipment installed no later than 5 years ago quantifies the technological structure of the hardware stock and reflects recent investments into process innovations. To take account of other than equipment-related production technologies, we condition the measurement of the technological structure of equipment by the positive answer to the question about the introduction of new or significantly modernized technologies.

Table 1 shows how our main performance indicators of interest differ across innovating and non-innovating firms between 2014 and 2016. Additionally, Figure 1 presents a more detailed graphical analysis of our data for exits using the Kaplan-Meyer survival estimator across various groups of plants depending on their innovation status and R&D spending.

R&D spenders exhibit the most consistent advantages in all performance indicators: they beat non-spenders in technological efficiency, labour productivity, growth rate, and survival. The Kaplan-Meyer estimator (Figure 1) shows the same tendencies: starting from the central point in the survival time, the product innovators, process innovators, and R&D spenders are more likely to survive than are non-innovators.

The return to process innovation is the highest in labour productivity and survival, while the technical efficiency is only slightly higher for process innovators. And at last, all types of innovators have much larger plants than non-innovators, the gap being the highest for process innovators where firms which introduce new technologies employ nearly 2.5 times more people than inactive firms. These results illustrate patterns of performance by innovators in the Russian manufacturing industry and need to be tested by our further econometric analysis.

3.4. Controls

The literature recognizes various determinants of R&D and innovation which we include in the knowledge production function as controls and divide them into three groups: firm-level knowledge stock, ownership and organization, and the industry's technological and demand conditions.

With regard to knowledge stock, we include a variable which measures investments into human capital as a dummy for firms which invest into personnel training (24.7% of observations). Age may capture the accumulated knowledge through learning and lead to improvements in innovation, productivity, and growth (Coad, Segarra, and Teruel 2013), though the underperformance of younger firms may be associated with their riskier R&D strategies when compared to mature firms rather than being derived from their low knowledge stock (Coad, Segarra, and Teruel 2016). Our sample is dominated by mature firms: the mean age of the firm in the sample amounts to almost 18 years.

ICT capabilities measured as a dummy for firms which report ICT management system (14.6% of observations) may contribute to innovation decisions due to additional IT-based capabilities, lower operation time, and a higher efficacy of managers. The international quality management certificate (ISO) has an impact on product and process innovations through its incentives to update technologies and improve quality (Marette and Crespi 2003).

We control for the size of the plant measured in terms of employment as a continuous and categorical variable or as logged operational turnover in the equation for growth effects. The firm's market power is measured as a share of firms' turnover in the total industry's turnover at the 4-digit sectoral level. As a rule, the empirical literature confirms the Schumpeter hypotheses of size and monopoly power and reports that large plants are more likely to innovate and to receive higher return from innovation to productivity, but their innovation output does not increase proportionally to their size (Griffith et al. 2006; Mairesse and Mohnen 2010). The mean plant in the sample employs 99 people in the

time covered by the survey (2014)[4]; between 2011 and 2016, the mean employment declined from 141 to 100 workers.

Several features, controlling for firm organization, are captured by the ownership structure. We expect that the foreign subsidiary has advantages in terms of productivity (Melitz 2003), but is not necessarily a superior innovator if R&D and innovation decisions are taken at the level of the home multinational (Crespi, Tacsir, and Vargas 2016). Government ownership has an inconclusive impact on innovation decisions. On the one hand, the management of a publicly owned organization has weak incentives to take decisions that lead to cost reduction or innovation (Hart, Shleifer, and Vishny 1997). On the other hand, the state sector is still an important actor in technological development, seeing as state-owned firms can more easily obtain financing support, innovation subsidies, and preferential access to the new markets than can private firms. Literature on emerging economies' data mostly shows that firms innovate less if the government keeps a stake (Cui, Jiao, and Jiao 2016). In addition to providing us with an ownership dummy, our data allows to measure access to public support. Subsidies may stimulate innovation by yielding additional resources to the firm (Mairesse and Mohnen 2010) or by creating rents and reducing the firm's incentive to improve efficiency (Cette, Lopez, and Mairesse 2017). In our data, about 3.6% of firms receive subsidies, larger firms being much more effective at getting subsidies (59% subsidized firms in the group of large firms).

The dummy for the holding answers for the external economies of scale, which is usually an attribute of an integrated company and simultaneously measures the level of independence of firm behavior because the holding may delegate the R&D and innovation decisions to a specialized facility. The share of the main product in sales (specialization) takes account of the finding by (Bernard, Redding, and Schott 2010) that a firm's productivity is positively linked to the variety of products it produces.

We control the estimations for financial constraints experienced by the firm (lagged negative profit dummy), taking into account the argument

[4] According to the Ruslana data

of Schumpeterian literature that profits play a role in innovation decisions of the entrepreneur as part of the “virtuous circle” when profit is the result of successful innovation and the source of financing of the innovation effort (Guarascio and Pianta 2017). Financial frictions prevent firms from developing and adopting better technologies (Gorodnichenko and Schnitzer 2013), though access to external financing (measured in our data as a dummy for firms which use external funds) may increase investing capabilities.

<< Table 2 about here >>

Sector dummies are used to control for unobserved sectoral heterogeneity and to take account of various technological opportunities within sectors. The variety of technological opportunities, as evolutionary theory shows, may stem from the population ecology approach, obtaining when shared resource pools affect firms belonging to one niche, i.e. industry, in the same way (Geroski et al. 2003; Hannan and Freeman 1977). In some specifications, we replace sector dummies by specific sectoral characteristics like the entry rate (the share of entries in the total number of active firms in 4-digit sector) or the deflated sector output growth rate. This allows us to control for external forces possibly acting on innovation decisions of the firm and the efficacy of these decisions, especially for demand-oriented innovation. The entry rate captures industry evolution when the incumbents may be challenged by start-ups which enter with new technologies and therefore the higher entry rate may be associated with an additional motivation for mature firms to innovate. The average output growth at the sectoral level helps to capture the stage of the business cycle and demand conditions in the sector.

The role of competition in innovation decisions is complex, being mostly positive for technologically advanced firms near the frontier and nil or negative for laggards (Aghion et al. 2006). We expect positive impulses from competition, for which we use a self-reported categorical variable showing the pressure of competition from foreign subsidiaries and imports on the markets where the firm is active. Exporting firms are more likely to innovate and report R&D expenditures due to the pressure of higher

competition in international markets and the learning effects (Gorodnichenko et al., 2010).

The access to external knowledge is proxied by the strength of agglomeration forces, depending on the size of the host city. The city size may determine innovation and productivity because proximity contributes to a more effective generation and diffusion of knowledge (see Feldman 1999 for literature survey). Table 2 summarizes definitions of dependent variables, main predictors of interest, and a set of controls at the firm and sector level.

4. Empirical model

4.1. Research design and identification strategy

We begin by constructing the measure of firm productivity with maximum-likelihood estimates of the stochastic frontier production function for panel data, as suggested in (Battese and Coelli 1995). The advantage of this measurement is that it takes account both of technical progress and inefficiency of the plant relative to the best performing plant in the sector. Given that the registry data which we link to the survey data is extracted from the Ruslana database, we also followed the advice of the (OECD 2017) on how to approximate indicators not observed directly in this data base, but which are needed for a production function analysis. Thus, we proxy output, capital, material, and labor cost by turnover, fixed assets, cost of goods sold and the average wages at the sector/region level, because the plant level labor cost data is too scarce. Then we exclude the missing observations and trim the 1% worst and best plants at the TFP level to exclude the outliers. The final full unbalanced population panel includes 471,740 firms across 231 4-digit manufacturing sectors. For each of the surveyed plants we construct the indicator of the TFP distance to the technological frontier as a share of plant TFP relative to the best performing plant in the 4-digit sector.

In all further specifications except for the survival equation we use an extension of the three-stage structural model developed by (Crépon, Duguet, and Mairesse 1998) (CDM) and later modified by (Lööf and Heshmati 2006). We depart from this classical model with two important

novelties: we add imports as an input into the knowledge production function and continue the CDM logic into the growth equation when growth is influenced by productivity gains achieved due to innovation. Figure 2 shows the research model we apply in this study when the system of four equations is estimated for several sequencing stages of the innovation cycle: the decision to undertake R&D, to introduce product or process innovation, the resulting outcome for productivity, growth, and survival.

<< Figure 2 about here >>

The main starting point of CDM analysis comes from the assumption that R&D data systematically underestimate the amount of R&D efforts and innovation, especially within smaller firms, which often innovate on a more informal basis outside of the R&D lab (Dosi 1988). If so, using predicted rather than observed values of R&D and innovation efforts helps to take account of formal and informal activities.

Additionally, several econometric problems, typical for the innovation-productivity analysis, are addressed by CDM approach. First, it deals with the selection bias occurring when R&D spenders and innovators are not randomly selected from the manufacturing firms' population and the decision to undertake R&D and R&D intensity are not fully independent. When modelling the selection of innovation input, we solve this issue by additionally considering a selection equation and therefore allowing for a possible dependence between the first two stages of the system of four equations.

Second, the studies of innovation-performance link on the survey data face difficulties in the interpretation of correlation and in defining the direction of causation because one cannot ignore that more productive firms are more likely to engage in R&D and be successful in the area of innovation output. Therefore, the real causation may go from productivity to R&D and innovation. When factors underlying selection into R&D spenders are accounted for, explaining R&D intensity on a reduced sample of firms which report R&D reduces concerns about endogeneity.

Thirdly, the strength of this study lies in the possibility of a chronological sequence of the analysis. Usually, innovation papers suffer

from the simultaneity bias because of the cross-sectional nature of the survey data. Thus, innovation input in t is often used as an explanatory variable for the innovation output in t, and the innovation output, in turn, as a determinant of the productivity, also in t. However, previous productivity in $t-1$ probably determines innovation in t as well. In order to break this econometrically vicious circle, we combine cross sectional data for selection and outcome equations, and panel data from various sources for the innovation output-performance link. Lagged levels of TE among controls additionally lessen endogeneity issues and help to study how previous productivity supports further innovation.

To sum up, our research explains the decision to undertake R&D, the innovation output, and the resulting performance indicators: productivity, growth and survival. Each stage of the three-stage CDM model is explained in detail below.

4.2. R&D decision and R&D intensity

First, following (Griffith et al. 2006) and (Morris 2018), we estimate the decision to undertake R&D and the R&D intensity within the two-step Heckman selection procedure for the cross-sectional data structure. Our aim is to obtain the latent measurement of R&D input into the knowledge production function, based on the assumption of the existing recording and/or reporting problems associated with the formal R&D expenditures in firms' books. The sample selection model can be specified as follows:

Let g_i^* be a latent (unobserved) firm's decision relating to whether or not to undertake an innovation effort and let r_i^* be its latent (unobserved) level of innovation investment, with g_i and r_i being their observable counterparts. Then,

$$g_i = \begin{cases} 1 \; if \; g_i^* = \beta_0 x_{0i} + \mu_{0i} > 0, \\ 0 \; if \; g_i^* \leq 0 \end{cases} \qquad (1)$$

and

$$E[r_i | g_i = 1, x_{1i}\,] = E[r_i | r_i^* > 0, x_{1i}] = \beta_1 x_{1i} + E[\mu_{1i} | r_i^* > 0, x_{1i}] \qquad (2)$$

where x_{0i} and x_{1i} are vectors of determinants. β_0 and β_1 are parameter vectors which measure the impact of various factors on the probability of

undertaking an R&D investment in the first place and its level respectively. We assume that μ_{0i} and μ_{1i} are normally distributed random error terms with mean of zero, that they have constant variances, and that they are uncorrelated with the explanatory variables and correlated with each other. Their joint distribution is bivariate normal.

In the first stage, a binary variable g determines whether or not r is observed. We estimate x_0 using Probit. In the second stage, we estimate β_1 of the second stage using OLS, but conditional on $g_i = 1$, i.e. $r_i > 0$. For observed values $g_i = 1$, we have an observed realization of the other latent variable r^*.

Both x_0 and x_1 include sector dummies, a training dummy as a proxy for human capital, an internationally recognized certificate (ISO), and the ownership structure as predictors of R&D decision and R&D intensity. If a firm undertakes R&D, the intensity of R&D expenditures is measured as a logarithm of R&D expenses in sales per worker (averaged for 2011-2013).

For a more robust specification, we impose exclusion restrictions, meaning that the selection equation includes exogenous variables that are excluded from the outcome equation (Cameron and Trivedi 2010). In the absence of the exclusion restriction, a multicollinearity issue might potentially arise due to the almost linear form of the inverse Mill's ratio over the considerable portion of its range: in case of collinearity existing between the correction term and the included regressors, standard errors are heavily overestimated. The size of the plant is a state-of-the-art exclusion restriction in the selection equation and is measured as logged average employment between 2011 and 2013. It is not included in eq. 1 because R&D intensity has already been explicitly scaled (Morris 2018). The possible explanation is that smaller firms possess fewer financial resources and a stronger risk aversion towards innovation activities as compared to large firms (van de Vrande et al. 2009). Two other parameter shifters, exporting and foreign competition, are relevant for decision on R&D spending, but are excluded from the R&D intensity equation.

Thus, we predict the value of R&D expenditure per employee, save the predicted values of the R&D intensity and the inverse Mills ratio, and use it as an instrument in the next step when estimating the knowledge production function.

4.3. The knowledge production function

The third equation within the CDM framework is the knowledge production function that links innovation output to productivity. It can be formalized as follows:

$$K_{it} = \gamma_r \widehat{R_{it}} + \beta_2 Y_{it-1} + \beta_3 X_{2it} + \beta_4 MR + \mu_{3t} \quad (3)$$

where K is the innovation output, R is the latent innovation input, Y is the previous productivity, X is a vector of controls, MR is the inverse Mill's ratio from eq. 1-2, and μ is the random error term with a zero mean and constant variance.

We include the inverse Mill's ratio to control for the selection bias. We also account for firms which might have attempted some innovations but don't report it explicitly in the survey by including the predicted values of R&D intensity.

To estimate an alternative specification of the knowledge production function, we also make use of importing intensity as a proxy for knowledge input. We assume that import is not a latent variable, therefore, we just employ observed values of import intensity and do not correct for the selection bias and therefore omit the inverse Mill's ratio

$$K_{it} = \gamma_r I + \beta_2 Y_{it-1} + \beta_3 X_{2it} + \mu_{3t} \quad (4)$$

where K is the innovation output, I is the observed innovation input, Y is the previous productivity, X is a vector of controls, and μ is the random error term with a zero mean and constant variance.

4.4. Performance equations

At the last stage of the CDM model we assess the impact of the innovation input on the performance:

$$Y_{it} = \gamma_k \widehat{K_{it-1}} + \beta_5 X_{3it} + \mu_{4t} \quad (5)$$

where Y is a firm's performance indicator, γ is the performance' effect[5] with respect to product or process innovation, K is the predicted innovation from the previous step, X is a vector of controls, and μ is the random error with zero mean and constant variance.

In eq. 5 three alternative measures indicating firm's performance are used: technical efficiency, labor productivity and output growth. To account for a plausible chronological sequence of the innovation process, allowing for a feedback effect between productivity and innovation, the dependent variable is modelled as a function of the lagged predicted innovation output (product and process innovation). We control eq. 4 and 5 for a number of factors such as: size, age, ownership, specialization, liquidity, market share, location, and sectoral dummies.

In case of output growth, we use the sectoral growth rate on the NACE 4-digit level instead of sectoral dummies. In line with Gibrat's law (Gibrat 1931), we proxy size by previous output. Further on, we exclude market share and limit the sample to surviving firms only.

Following (Lööf and Heshmati 2006), we allow for a partial correlation of the error terms within the CDM model by assuming that the main predictor's (innovation output) error terms are correlated with the independent endogenous variable (TE, labor productivity, and output growth). Therefore, equations 3, 4, and 5 are modelled as a simultaneous system using instrumental variables two-stage least squares (IV 2SLS) in the panel data setting for the post-innovation period of 2014-2016. To sum up, we assume that productivity in 2014 was influenced by innovation output from 2013 and this output in turn was affected by the productivity level in 2012. Thus, we account for the endogeneity of innovation output and a firm's productivity.

[5] Only in case of labour productivity and product innovation can we speak of elasticity, whereas it is not possible to talk about elasticities when measuring a firm's performance by TE or the impact of process innovation on TE or labour productivity (see Table 2 for a construction of the variables).

4.5. Survival function

As a further performance indicator, we estimate a firm's survival as depending on productivity and growth advantages. For this purpose, we estimate proportional semi-parametric Cox proportional hazard regressions, which relates the survival time of the firm to other performance and innovation indicators: technical efficiency, labor productivity, product, process innovation, and R&D intensity. The model produces estimates of the hazard rate, i.e. the instantaneous rate of failure at which a subsidiary i will exit at time t on the condition that it survived at $t-1$.

In order to obtain the hazard rate of firm i at time t, $h_i(t)$, the non-parametric baseline hazard function, $h_0(t)$, is multiplied by a parametric part capturing the impact of the vector of covariates $X_{ik}(t)$ by means of parameter estimates b_k.

$$h_i(t) = h_0(t) exp\left\{\sum_{j=1}^{n} b_j P_{ij}(t) + \sum_{k=2}^{m} b_k X_{ik}(t)\right\} \quad (6)$$

The vector of main predictors P, individually comprising innovation and performance indicators, is used in the equation together with the vector of covariates X: size, age, liquidity, specialization, market share, and organization on the firm-level and some further controls (size of the city and entry share in the 4-digit sector). In one specification, we interact innovation with the size dummy to study if innovation may help most vulnerable small firms to decrease their mortality rate.

5. Results and Discussion

5.1. Knowledge production function

Our first step is to estimate R&D knowledge input by means of the Heckman procedure. Table 3 presents results on the likelihood of the decision to undertake R&D (column 2) and the value of R&D expenditures per worker (column 1). As explained in our methodological section, the two-stage procedure to define the input into innovation output is essential because we imply selection and expect that some manufacturing firms underreport R&D expenditures. Our results confirm the selection bias: the coefficient on lambda (inverse Mill's ratio) is significant at the 5% level,

which implies that error terms are correlated. Therefore, traditional methods with OLS estimation would be misleading in this research.

The propensity to undertake R&D increases with the size of the plant and is more typical for industries with the higher value added, firms in food-processing and timber industries being significantly less likely to take an R&D decision relative to chemicals (our reference category). In line with the Schumpeterian prediction concerning the role of firm size in concentrated markets, in our data a growth of the number of employees by 1% is associated with a 3.1% increase of the likelihood of an R&D decision. Thus, our finding confirms that the production of knowledge is a subject of scale economy. We therefore use size to explicitly control for selection bias and furthermore assume the linearity of the investment function with respect to size. Therefore, it is omitted from the second stage equation explaining R&D intensity.

A greater knowledge stock is associated with a higher likelihood of performing R&D: if the firm reports personnel training, the likelihood of an R&D decision increases by 13.5%. International quality certificate and the power of foreign competition strongly determine an R&D decision. Our result on exports compellingly confirms a positive relation between R&D and exports, where being an exporter correlates with a 12% higher probability to invest in R&D. This result stays in line with the CDM-based literature, which reports a higher probability of investing in innovation for exporting firms. Thus, (Crespi and Zuniga 2012) report an 11% marginal effect of exports on R&D decision for Chile and 15% for Argentina. The economic significance of this effect for developed countries is somewhat higher: 65% for UK ((Hall and Sena 2017) and 64% for Belgium ((Czarnitzki and Delanote 2017).

<< Table 3 about here >>

The ownership structure and organization are weakly related to R&D. Comparable results on size, competition, and ISO as drivers of R&D decision in the Heckman equation can be found in (Morris 2018) for a big group of transition and developing economies.

Next, we estimate the knowledge production function (equation 3) and use the predicted value of R&D expenditures per worker and observed imports per worker as indicators of knowledge input into innovation output. We consider two different outputs: product and process innovations. Additionally, we control the model for previous technical efficiency (columns 1-4 in Table 4) and previous labor productivity (columns 5-8) as drivers of innovation to test our hypothesis concerning incentives to innovate generated by economic return from previous innovation. As results from Table 4 indicate, our choice of two-stage models is fully justified: the significant Mill's ratio suggests selectivity across all specifications in equation 1.

The economic significance of the knowledge input is the highest for product innovation. When R&D expenditures per worker grow by 1%, new products' sales per worker increase by 1.95-1.11% (columns 1 and 5). The contribution of imports is somewhat lower when compared to R&D, though it remains positive and significant: if lagged imports, measured as the value of imported machines and equipment per worker, increase by 1%, sales of novel products per worker grow by 0.5%.

In the same way both R&D and imports translate into process innovations, though its effect is smaller when compared to product innovation and we do not observe a meaningful difference between the two knowledge inputs. The share of new equipment in the hardware stock conditional on a positive answer to the question about the introduction of new technologies (our definition of process innovation) increases by 0.8-0.6 percentage points with a 10% increase of R&D intensity and by 1-0.8 percentage points with a 10% increase of imports. The lower elasticity of process innovations to knowledge inputs may be caused by a low sensitivity of revenue-based indicators to efficiency improvements, associated with the modernization of hardware and production technologies (Hall, 2011).

It is also the case that innovation output is higher for the most productive firms, both for TE and labor productivity specifications. The shortening of the distance to the technological frontier by 1 percentage

point, or 0.01 unit, (the TE ranges from 0 to 1, where the 1, or 100%, is the frontier), leads to a 2-35-3.65% growth of product innovations. Less powerful is the impact of achieved labor productivity on product innovations, where a 1% gain in labor productivity results in a 0.19-0.27% growth of product innovations. Effects of previous levels of productivity on process innovations are less consistent and somewhat “noisy”. Summing up, the results confirm our H2 for product innovations and demonstrate the sequence of evolutionary knowledge creation, whereby efficient innovation, proxied by technological superiority and higher labor productivity, reinforce further innovation.

Some controls are also important determinants of innovation output outside their effect on R&D. Thus, smaller firms are not only less likely to perform R&D, but they are also less efficient in translating R&D into successful product or process innovations. Firms under foreign ownership, being neutral for R&D decisions, are significantly less innovative in the case of product innovations. This result could capture the specificity of the markets the foreign subsidiaries are targeting and the distribution of labor in the international value chain they belong to because subsidiaries may rely on the innovations carried out by the headquarters (Crespi, Tacsir, and Vargas 2016). Market share (not included in R&D equation), as a rule, significantly increases innovation output in line with the Schumpeterian hypothesis on the advantages of dominating firms in innovation efforts.

A location in a large city significantly increases innovation output for product innovation irrespective of the source of the knowledge input and is not significant for process innovations. Thus, we confirm the power of agglomeration forces and the importance of the local market size for more demand-driven product innovations.

The firms which belong to the sectors characterized by higher entry rates do not innovate more intensively, contrary to our expectation based on evolutionary theory. Thus, we could not confirm that new entrants threaten the technological leadership of mature incumbents and thus incentivize their innovation behavior.

<< Table 4 about here >>

<< Table 5 about here >>

Weak innovation efforts of entrants may be inferred from the results on how age determines innovation: younger firms in all specifications are significantly less innovative. This may partly explain our result on the neutrality of the industrial dynamism as measured by the entry rate as a determinant of innovation.

5.2. The effects of innovation on TE and labor productivity

Next, we study whether innovation leads to technological progress of the firm and productivity gains as described in equation 5. In this way we test our main hypothesis concerning the innovation-productivity link (H1). We take into account that the knowledge stock, a firm's organization, ownership, and other covariates included in the analysis affect both innovation and its efficacy in terms of productivity growth and estimate productivity equations as a system of two stage 2SLS, where all regressions are IV regressions. Table 5 reports the second stage results for two outcomes: TE and labor productivity[6]. As in previous specifications, we distinguish between two sources of knowledge input: predicted R&D intensity and imports, and two types of innovation.

The results show that product innovation has a strong effect on TE: if innovative sales per worker increase by 10%, the distance to the technological frontier shortens by 1-2 percentage points. Process innovations are somewhat less beneficial for TE and contribute to technological advances only when we measure knowledge input by imports.

Referring to labor productivity, both types of innovation irrespective of knowledge source make firms more productive: the elasticity of labor productivity in relation to product innovation accounts for 0.37-0.55%. This result is consistent with the finding by (Roud 2018) for Russian firms on CIS data (he reports a mean 0.3% elasticity ranging from 0.1% among so called national innovators to 0.4% among international innovators).

[6] The first stage IV results are available from the authors upon request

Comparable estimations for 18 OECD countries produce an elasticity of 0.3-0.7% (Criscuolo 2009).

The effect of process innovation on labor productivity is high: a radical improvement of the technological structure of the hardware stock, such as a doubling of the share of machines and equipment installed no later than 5 year ago conditional on a positive answer to the question about the introduction of new technologies, leads to a 7-8% increase of labor productivity. The established large coefficient (when compared to peers) for process innovation with respect to labour productivity compared to peers[7] is explained by our measurement strategy where we did not use a conventional process innovation dummy, typical for most studies, but instead quantified it by recent investments in machinery and equipment – the standard source for technologies among Russian manufacturing firms.

The implication of our results for productivity equations is that product innovation is most beneficial as a tool to increase TFP and shorten the distance to the frontier, while process innovation, which mostly rely on knowledge embodied in new hardware stock, critically increases labor productivity.

Regarding the remaining control variables, it is remarkable that subsidized firms are significantly behind other manufacturing firms in TE. This finding brings with it some implications concerning the focus of innovation policies. Foreign subsidiaries, which were not found to be superior innovators, nevertheless lead in technical efficiency and labor productivity, well in line with the theory by (Melitz 2003). Younger firms trail behind incumbents in TE.

5.3. Growth equation

In this section, we estimate the growth effects of innovation and productivity gains on the short panel of post-innovation performance – the econometric method which is found most appropriate for high-frequency

[7] The finding that product innovation are more beneficial for labor productivity than process innovation are reported in (Crespi, Tacsir, and Vargas 2016) (36 vs 19 %) and (Morris 2018) (30 vs 13%) though in both papers process innovations were measured as dummies.

variations in a firm's growth rates (Geroski et al. 2003). We address the issue of the endogeneity of innovation and productivity by estimating the IV 2SLS model, thus expanding the logic of the structural multistage modelling to the growth equation[8]. In this part of the study, only firms that are in existence in the beginning and at the end of the observation period have been examined to avoid selection bias. The determinants of survival are studied separately in the next section 5.4. to check if the impact of innovation on growth is not biased by the higher mortality of risky innovating firms. The main variables of interest are product and process innovations in t-1 period and achieved technical efficiency. In this way, we aim at separately analyzing the effects of innovation and technical efficiency, the last we believe to be a mechanism to transmit innovation impulse to growth (Nelson and Winter 1982b). All regressions are controlled for the real mean growth rate at the 4-digit sectoral level to account for the business cycle, which could have driven the growth dynamics of firms in turbulent years (Table 6).

<< Table 6 about here >>

Both product and process innovations produce a significant improvement in the growth performance of manufacturing firms: a 1% increase in the share of novel products' sales per worker is associated with a 0.05% increase in the growth rate. Process innovations are somewhat less beneficial for growth with a 0.02% effect. Contrary to expectations, technological superiority, achieved as a result of product and process innovation, is not advantageous for growth (the coefficient on TE is positive, though insignificant). The lack of positive causation between TE and growth may reflect the general inefficiency of allocative mechanism in the Russian manufacturing industry, where firms that could exploit scarce resources in the most efficient way have limited access to

[8] We have also experimented with quantile regressions, which are extensively used in growth analyses on microdata based on the assumption about the conditional distribution of growth rates (Coad and Rao 2008; Distante, Petrella, and Santoro 2018). However, the coefficient estimates on our data remain more or less constant across various quantiles.

resources and therefore are not able to unfold their full productive potential (Coad 2009).

Industry dynamics are the most influential factor which determines firm growth: an increase in the sectoral growth rate by 1% leads to an increase in the firm growth rate of about 0.25–0.66%, depending on the specification. Thus, our study confirms that the performance of firms is critically shaped by the conditions of technology and demand in underlying industries (Audretsch and Mahmood 1995; Audretsch 1991) and that innovation is an important, if only second-rate factor contributing to growth.

As far as the size-growth connection is concerned, when we measure the size by the real lagged sales, we find that smaller firms grow faster conditional on their survival. Age is beneficial for growth when size is controlled for: the finding is not supportive of the "bad controls" argument (Angrist and Pischke 2009; Coad 2018), whereby the advantages which come with age are controlled by the size. Our result also suggests that there is no clear evidence for the validity of the Gibrat's law (Gibrat 1931) on the basis of our data. The change in firm size is not independent from its initial size.

5.4. Does innovation support survival?

Table 7 shows the regression results estimating the survival time of the surveyed manufacturing firms. The post-innovation survival was tracked three years after the survey was conducted. We use the Cox proportional hazard model and report hazard rates - the rate of failure at which a firm will exit at time t on the condition that it survived at $t-1$. The aim of this examination is to test the H4 which expects innovation and productivity gains to increase survival time. Moreover, we also seek to confirm the power of our previous results regarding the growth equation, which was estimated on the subsample of surviving firms in order to preclude the selection of non-innovating firms into survivors. First, we report the hazard rates of firms depending on their R&D intensity (column 1), product (3) and process innovations (5), technical efficiency (7), labor productivity (9), and growth rate (11). Additionally, building on the previous literature which establishes higher mortality rates among small firms and

overall significant structural barriers to survival erected by low economies of scale (Audretsch 1995), we seek to understand if innovation and productivity gains condition the survival of small firms. For this, we use the same proportional Cox-Hazard model and add interactions of our main predictors of interest with a dummy for the small size of the firm (columns 2, 4, 6, 8, 10). We use the universal set of controls, which capture the market share, location, and firm-specific characteristics such as ownership, economies of scale, and specialization. Industrial dynamics proxied by the entry rate at the 4-digit sectoral level suggests that the exposure of manufacturing firms to risk of failure are smaller in highly dynamic expanding sectors.

Our main finding from estimating eq. 6 is that there is a significant survival premium conferred by product innovation: the survival time increases for firms which are persistent in the introduction of new products to the market and manage to build a new product market portfolio rather than make minor refreshments of the product line: if the firm increases the sales of novel products per employee by 1%, the survival time increases by 5.7%. The hazard rate of exit is negative for all our main predictors of interest, though it is not always statistically significant: neither for R&D expenditures, nor for process innovation.

However, labor productivity strongly determines firm demography. A 1% increase in labor productivity decreases the hazard rate by 30%. The productivity advantage, measured through TE, is also positively, though not significantly, related to survival time (while controlling for profitability). It means that exiting firms do not necessarily have a lower efficiency than surviving firms, as is the case if the selection mechanism functions well. Therefore, the argument of the evolutionary literature according to which innovators can improve their survival chances as a result of higher efficiency (Grilishes, 1979) holds only partially — namely for labor productivity — in our data.

Table 7 also reports that the firm growth rate has a positive effect on survival (column 11). Comparable results are reported in the relevant literature (Cefis and Marsili 2006; Ugur, Trushin, and Solomon 2016).

The estimated hazard rates for industry dynamics, measured by the entry rate at the 4-digit sectoral level, are negative and highly significant, indicating that firms grouped in dynamic sectors with increasing demand tend to have a low hazard of exit. This result is consistent with (Foster, Haltiwanger, and Syverson 2008) and finds that demand variations across producers are the dominant factor in determining survival.

The controls have the expected signs: the survival time increases for profitable firms and for firms which report larger market share, while specialization and ownership do not matter.

Next, we study whether the gap between the firm size and the minimal efficient scale, which is found to be critical for survival in the literature (Audretsch 1995), shrinks when the firm innovates and achieves productivity advantages. Table 7 shows that our measurement of R&D intensity interacting with the dummy for the small size of the firm is negative and significant (column 2), meaning that a growth of R&D intensity by 1% increases the survival time of the small firm by 62.8%. Similar effects are observed for product innovation and labor productivity. Neither process innovation, nor TE and growth improve the demography of small firms. These results demonstrate that small firms, being most vulnerable to disinvestment risks, live longer when they undertake R&D investments and sell new products. The finding that innovation is most beneficial for the survival of small firms may also be found in (Cefis and Marsili 2006) in the case of Dutch firms, who also report that small firms are the most exposed to the risk of exit and that they benefit most from innovation as it relates to surviving in the market.

To sum up, we find that innovation is efficient in reducing firms' exit probability, though the effect is weaker than the economic return from innovation in terms of productivity and growth and is mostly important for small firms.

<< Table 7 about here >>

6. Concluding remarks

Raising productivity and changing the production structure remain the main challenges transition economies are facing. This paper aims to find new evidence concerning the effects of innovation on the performance of the Russian manufacturing firms and presents an empirical comparison of economic payoffs from various sources of knowledge input and for different types of performance. The available support of the predictions of the evolutionary literature on the Russian data is minimal and non-conclusive. Manufacturing firms are regarded as weak innovators focused on technology adoption and positioned far from the technological frontier, operating in a fragile economic and institutional setting. All this may suggest a low significance of innovation in catching up and growth, as is often the case in other transition and developing countries (Hall and Mairesse 2006). On the other hand, imitation and low risk strategies may have some rationale, since technological progress foreshadows a different use of inputs at different levels of development (Vandenbussche, Aghion, and Meghir 2006).

The findings in this paper provide new arguments regarding the process of knowledge evolution in the context of an emerging economy. The innovation-performance link in Russia does not differ much from the regularities established in the literature for other countries: firms that invest in R&D or learn from knowledge embodied in imported hardware are superior innovators; innovating firms are furthermore superior in labor productivity and technological efficiency. Innovative and productive firms are more likely to survive and grow conditional on their survival. However, weak market selection mechanisms and an inefficiency of resource allocation has some consequences: greater technical efficiency is not rewarded by growth and survival.

There are several remaining problems concerning Russia's technological development. The government still controls a large share of research resources and this hardly helps the technical upgrading of manufacturing firms. Our data confirm that neither subsidized nor government firms stay at the forefront of innovation. In general, firms respond weakly to government initiatives and the policies involve private

firms incompletely. This may be partly explained by the obvious mismatch between the government tools to stimulate technological progress and the actual tools which the firms use for technological upgrade and growth. Thus, the government mostly seeks to support large and high-tech projects in the inward-looking policy environment and largely overlooks mid-tech innovation and technology adoption. Our research shows that firms' behavior conforms to more fundamental economic incentives than the ones considered by government policy and that knowledge is generated through in-house R&D and imports in the presence of stronger foreign competition and trade integration.

Next, this paper confirms that economies of scale, both internal (size of the firm) and external (size of the host city) decide the successful conversion of knowledge input into innovation and innovation into productivity. Only a handful of advanced locations which generate agglomeration forces (large cities at most) host efficient innovators. Therefore, the policy of mushrooming technoparks in distant locations seems to disregard this reality.

We consider there to be some limitations of the data and research. First, our dataset is biased towards larger firms. Our econometric approach addresses the problem of underreporting of R&D expenditures by smaller firms in the survey but is not able to cope with underreporting of SME accounting data, while the estimations of performance are conditional on data availability. Weighting is only partly helpful because the actual full population of small firms is simply not known. Next, some inconsistency in the data may be caused by the absence of a full set of disaggregated deflators (firm level prices are always unobserved). This is an issue which could result in the mis-measurement of growth indicators during periods of high economic turbulence. Therefore, we urge caution in the interpretation of growth results because the variation of growth rates may be partly caused by a variation in input price dynamics. A short panel for productivity and growth equations may also underestimate the notion that firms have natural life cycles (Binder, Hsiao, and Pesaran 2005).

There are various extensions to the line of research suggested in this paper. A longer time period of analysis may bring additional insight and allow the use of a more nuanced econometric methodology because firms in our dataset were severely hit by exogenous destructive shocks which obviously interfered in the innovation-performance link. It would be interesting to find out whether the obtained results hold for a growing rather than for a stagnating industry when the growth is balanced by commodities' prices and more favourable terms of trade. The duration of the performance effects of innovations is also an interesting topic for analysis, especially in a comparative perspective.

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Tables

Table 1. Group statistics of performance (2014-2016) of innovators and R&D spenders

	Product innovation within 3 years prior to the survey				Process innovators within 3 years prior to the survey				R&D within 3 years prior to the survey			
	yes		no		yes		no		yes		no	
	Mean	No. obs	Mean	No. obs	Mean	No. obs	Mean	No. obs	Mean	No. obs	Mean	No. obs
Employment, people	143.5	752	79.42	724	186.8	606	75.97	956	185.4	495	80.57	1,450
TE	0.703	563	0.680	450	0.695	480	0.691	593	0.688	387	0.685	922
Labour productivity, output in thousand RUB/person	1635	728	1111	678	2132	590	1080	899	1881	482	1175	1,372
Sales growth rate, %	-14.4	722	-20.5	654	-17.7	585	-19.2	875	-16.7	484	-18.0	1,327
Exit rate, %	7.6	159	9.4	197	4.7	98	12	251	2.3	50	19	398

Source: Survey data for innovations and Ruslana data derived from Bureau van Dijk for productivity, output growth, and exit. The monetary indicators are deflated at 2010 prices. Deflators were calculated with the use of annual 4-digit sectoral prices indexes, as reported by Rosstat.

Table 2. Descriptive statistics of dependent and independent variables.

Variable	Definition and source of data	Mean	Standard Deviation.	Minimum	Maximum
TE – technical efficiency	A ratio of observed TFP to the maximum TFP in the 4-digit sector. The higher the value, the closer the plant is to the production frontier. Own calculation through stochastic frontier analysis, Ruslana data for the full population of manufacturing firms	0.688	0.127	0.227	0.992
Labour productivity	Log of deflated output per worker. Own calculation on Ruslana data	6.703	1.139	-1.310	13.36
Output growth	Annual output growth. Own calculation on Ruslana data	-0.106	0.613	-6.779	3.238
Failure to survive	Dummy for firms which de-registered between the time of the survey 2014 and the last reporting date (2018), Ruslana	0.0729	0.260	0	1
Product innovation	Log of real new products' sales per worker. Calculated from the question about the mean share of new products' sales in total turnover during three years prior to the survey. Own calculation based on the survey data	0.366	4.340	-9.640	11.11
Process innovation	Share of recently installed machinery and equipment (< 5 years) if the firm positively responded to the question about the introduction of new production processes. Own calculation based on the survey data	0.116	0.248	0	1
R&D decision	Dummy for firms which performed R&D between 2011 and 2013, survey	0.171	0.377	0	1
R&D intensity	Log of real annual value of R&D expenditures per worker. Own calculation from the survey data	0.466	1.391	-0.728	8.968
ICT	Dummy for firms which have ICT management system, survey	0.161	0.367	0	1
Human capital	Dummy for firms, which trained personnel, survey	0.292	0.455	0	1
ISO	Dummy for firms which introduced ISO and other international quality certificates, survey	0.413	0.493	0	1
Exporting	Dummy for exporting activities, survey	0.154	0.361	0	1
Imports	Log of yearly real value of imports of machinery and equipment per worker. Own calculation based on the survey data	-2.352	3.047	-3.729	9.876
Age	Number of years on the market, survey	17.98	19.13	1	303
Specialization	% of main product line in sales, survey	79.74	21.68	3	100
Subsidized	Dummy for firms which received any kind of financial support from the government, survey	0.0367	0.188	0	1
Holding	Belongs to holding, dummy, survey	0.0897	0.286	0	1
Foreign	FDI among owners (any stock), dummy, survey	0.0234	0.151	0	1

Table 2. Descriptive statistics of dependent and independent variables. Continued.

State	Government among owners, any stock, dummy, survey	0.0254	0.158	0	1
Liquidity	Dummy on negative profit in the previous year, Ruslana	0.198	0.399	0	1
Market share	% of firms' sales in total sales of 4-digit sector. Own calculation on Ruslana data	0.0253	0.135	0	1
External financing	Dummy for firms which raised any external financing in 2011-2013, survey	0.375	0.484	0	1
Size group	Categorical variable for small (=3), medium (=2), and large (=1) subsidiaries, Ruslana	1.565	0.679	1	3
Size (alternative)	Log of employees, Ruslana	3.251	1.447	0	9.727
Foreign competition	Dummy for firms which experience any type of competitive pressure from foreign subsidiaries or imports, survey	0.395	0.489	0	1
Entry rate	Share of firms which entered the 4-digit sector in the total number of firms. Own calculation on Ruslana data	0.0731	0.0344	0	0.222
Industry growth	Yearly real output growth rate in 4-digit sector. Own calculation on Ruslana data	0.00695	0.174	-1.271	1.004
Size of the city	Categorical variable for cities with population less 250 thousand people (=3), 250 - 999 thousand people (=2), and above 1 million people (=1), survey	1.918	0.836	1	3

Note: Data are weighted and for 2014

Table 3. R&D decision and R&D intensity (average marginal effects)

	R&D per worker	R&D decision
Holding	0.623***	-0.004
	(2.81)	(-0.15)
Human capital	0.283	0.135***
	(0.97)	(6.20)
ISO	0.585***	0.060***
	(2.93)	(2.91)
FDI	0.119	-0.066
	(0.33)	(-1.46)
State	-0.523	0.004
	(-1.15)	(0.07)
Specialization	-0.004	-0.000
	(-0.77)	(-0.90)
Electro	-0.036	0.132*
	(-0.10)	(1.74)
Engineering	-0.085	-0.010
	(-0.27)	(-0.19)
Food	-0.137	-0.193***
	(-0.29)	(-4.39)
Other non-metallic	-0.664*	-0.061
	(-1.77)	(-1.04)
Steel	-0.480	-0.051
	(-1.46)	(-0.94)
Textile and garment	-0.960	-0.163***
	(-1.49)	(-3.17)
Timber	-0.091	-0.185***
	(-0.15)	(-3.88)
Transport	0.019	-0.071
	(0.05)	(-1.16)
Log of employees		0.031***
		(4.94)
Exports		0.120***
		(5.09)
Competition (FDI or import)		0.064***
		(3.12)
Lambda		0.638**
		(2.02)
Number of observations	1111	
Number of selected observation	217	
Rho	0.454***	
Sigma	1.404***	
p-value for comparison test	0.013***	

Notes: The results of the two-step Heckman procedure on cross-section average data for 2011-2013. The coefficients in the second column are for the likelihood of a firm to invest in R&D, in the first column those for the expected value of R&D intensity if the firm has reported R&D spending; Rho tests for the significance of the correlation term between the residuals of the selection and outcome equations; *t* statistics in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 4. The determinants of innovation output: by type of innovation and source of knowledge

	Controlled for lagged TE				Controlled for lagged labor productivity			
	Product innovation		Process innovation		Product innovation		Process innovation	
	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input
Lagged TE	3.651***	2.348**	0.055	0.067**				
	(3.70)	(2.49)	(1.64)	(2.07)				
Lagged labor productivity					0. 186***	0.266***	0.003	-0.002
					(4.23)	(4.10)	(1.20)	(-0.42)
Latent R&D intensity	1.951***		0.082***		1.114***		0.058***	
	(5.67)		(5.23)		(3.99)		(4.55)	
Mill's inverse	-0.660**		-0.022*		-0. 612***		-0.025**	
	(-2.55)		(-1.86)		(-2.97)		(-2.65)	
Lagged imports		0.518***		0.013***		0.116***		0. 080***
		(10.62)		(7.24)		(5.57)		(6.43)
ICT	0.990**	0.456	0.091***	0.057***	0. 759***	0.760**	0.071***	0.052***
	(3.23)	(1.56)	(6.50)	(4.36)	(2.75)	(2.96)	(5.72)	(4.33)
External financing	1.304***	0.783**	0.033***	0.018	1. 097***	1. 005**	0.033***	0.015
	(4.64)	(2.84)	(2.59)	(1.47)	(4.63)	(4.52)	(3.11)	(1.46)
Market share	2.217**	1.045	0.174***	0.127 ***	0.698	0.497	0.102***	0.100***
	(2.48)	(1.30)	(4.70)	(3.85)	(1.13)	(0.81)	(3.51)	(3.46)
Liquidity	0.331	-0.153	0.019**	0 014	-0.056	-0.088	0.002	0.003
	(1.00)	(-0.48)	(2.14)	(1.56)	(-1.06)	(-1.12)	(0.55)	(0.64)
Medium size	-1.297**	-0.969**	-0.036*	-0.055 ***	-0.247	-0.241	-0.010	-0.036**
	(-2.95)	(-2.31)	(-1.89)	(-3.11)	(-0.95)	(-0.90)	(-0.81)	(-2.76)
Small size	0.294	0.308	-0.004	-0.039	-0.306	-0.217	0.060**	0.005
	(0.30)	(0.32)	(-0.10)	(-1.04)	(-0.51)	(-0.40)	(2.23)	(0.18)
Age	-0.012**	-0.009**	-0.001***	-0.001***	-0.013***	-0.006	-0.001***	-0.000**
	(-2.89)	(-2.32)	(-3.87)	(-3.11)	(-3.15)	(-1.56)	(-3.36)	(-2.50)
FDI	-2.654***	-0.797	-0.200	0.028	-2.314***	-0.714	0.003	0.048**
	(-5.03)	(-1.58)	(-0.84)	(1.20)	(-4.38)	(-1.45)	(0.12)	(-2.50)
State	1.008	0.180	0.069**	0. 011	0.141	-0.236	0.034	-0.001
	(1.44)	(0.29)	(2.19)	(0.41)	(0.21)	(-0.41)	(1.15)	(-0.06)

Table 4. The determinants of innovation output: by type of innovation and source of knowledge. Continued

	Controlled for lagged TE				Controlled for lagged labor productivity			
	Product innovation		Process innovation		Product innovation		Process innovation	
	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input
Subsidized	0.172	-0.391	-0.024	-0.037*	0.387	0.055	-0.013	-0.023
	(0.33)	(-0.78)	(-1.01)	(-1.67)	(0.77)	(0.12)	(-0.58)	(-1.09)
Holding	-1.204**	0.182	0.000	0.035**	-0.455	0.423	0.020	0.043***
	(-2.90)	(0.56)	(0.03)	(2.41)	(-1.22)	(1.41)	(1.18)	(3.09)
City size 250 - 999 th.p..	0.280	-0.338	0.044***	0.012	-0.352	-0.519*	0.006	-0.001
	(0.81)	(-1.01)	(2.84)	(0.79)	(-1.24)	(-1.93)	(0.46)	(-0.05)
City size less 250 th.p	-1.074**	-1.834***	0.014	-0.011	-0.768***	-0.944***	-0.011	-0.017
	(-3.18)	(-5.72)	(0.90)	(-0.74)	(-2.72)	(-3.61)	(-0.87)	(-1.43)
Specialization	-0.003	-0.009	0.000	-0.000	-0.009	-0.014***	0.001**	0.000
	(-0.44)	(-1.35)	(1.16)	(-0.73)	(-1.60)	(-2.79)	(1.96)	(0.09)
Entry rate	0.991	-0.144	0.015	-0.060	0.920**	-0.181	-0.008	-0.052
	(0.30)	(-0.04)	(0.22)	(-0.83)	(2.42)	(-0.31)	(-0.41)	(-1.35)
Constant	-7.113***	0.124	-0.229***	0. 086**	-2.294*	0.180	-0.115**	0.129***
	(-3.91)	(0.14)	(-2.90)	(2.57)	(-1.70)	(0.27)	(-1.86)	(3.71)
Number of observatiions	1427	1519	1458	1583	2069	2156	2124	2243

Notes: The results stem from estimating the system of two -stage least-squares equations (2SLS on the panel data) for each year for the factors which affect product and process innovations depending on knowledge input through predicted R&D or imports. Only the second stage IV regressions are reported. TE refers to the TFP distance to the best performing plant in the sector and ranges from 0 to 1. *t* statistics in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 5. The impact of innovation on TE and labor productivity by type of innovation and source of input

	TE				Labor productivity			
	Product innovation		Process innovation		Product innovation		Process innovation	
	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input
Lagged product innovation	0.019***	0.011***			0.365***	0.548***		
	(6.15)	(5.08)			(4.75)	(7.77)		
Lagged process innovation			0.026	0.304**			6.631***	7.663***
			(0.29)	(3.13)			(4.27)	(5.90)
Medium size	0.038**	0.028**	-0.001	0.028	-0.668**	-0.678***	-0.769***	-0.744***
	(2.53)	(2.22)	(-0.06)	(1.49)	(-3.17)	(-3.44)	(-3.89)	(-4.80)
Small size	-0.041	-0.047*	-0.060	-0.035	-1.130**	-1.205**	-1.639***	-1.390***
	(-1.31)	(-1.71)	(-1.59)	(-0.97)	(-2.38)	(-3.05)	(-3.82)	(-4.80)
Age	-0.000**	-0.000**	-0.001**	-0.000*	-0.002	0.001	-0.001	0.001
	(-2.88)	(-3.07)	(-3.23)	(-1.83)	(-0.50)	(0.26)	(-0.43)	(0.61)
FDI	0.060***	0.029**	0.034	0.013	1.018**	0.589*	0.077	-0.121
	(3.59)	(1.98)	(1.62)	(0.58)	(2.38)	(1.66)	(0.21)	(-0.44)
State	0.031	0.046**	0.039	0.048*	0.066	0.287	-0.173	0.187
	(1.42)	(2.56)	(1.40)	(1.90)	(0.12)	(0.68)	(-0.37)	(0.67)
Subsidized	-0.028*	-0.031**	-0.022	-0.028	-0.069	0.035	0.260	0.319
	(-1.72)	(-2.15)	(-1.06)	(-1.34)	(-0.17)	(0.10)	(0.72)	(1.33)
Liquidity	-0.007	0.002	0.001	-0.007	-0.200***	-0.181**	-0.245***	-0.290***
	(-0.69)	(0.25)	(0.15)	(-0.76)	(-4.69)	(-3.14)	(-5.57)	(-4.99)
Holding	0.011	0.018**	0.016	0.011	0.029	-0.012	-0.242	-0.038
	(1.04)	(1.98)	(1.03)	(0.76)	(0.11)	(-0.05)	(-0.93)	(-0.22)
Market share	-0.081**	-0.035	-0.043	-0.065*	2.180***	1.290**	1.493**	0.355
	(-2.80)	(-1.51)	(-1.20)	(-1.89)	(4.41)	(2.87)	(3.07)	(1.02)
Specialization	0.001***	0.001**	0.000	0.000*	0.006	0.006	-0.002	-0.004*
	(3.33)	(2.86)	(1.39)	(1.72)	(1.18)	(1.54)	(-0.54)	(-1.67)
City size 250 - 999 th.p.	-0.074***	-0.073***	-0.079***	-0.078***	0.166	0.414**	-0.003	0.049
	(-6.97)	(-7.75)	(-5.56)	(-5.52)	(0.73)	(2.08)	(-0.01)	(0.35)
less 250 th. people	-0.005	-0.026**	-0.035**	-0.037**	0.390*	0.556**	0.137	0.143
	(-0.42)	(-2.64)	(-2.57)	(-2.69)	(1.65)	(2.75)	(0.66)	(1.03)

Table 5. The impact of innovation on TE and labor productivity by type of innovation and source of input. Continued

	TE				Labor productivity			
	Product innovation		Process innovation		Product innovation		Process innovation	
	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input	R&D as an input	Imports as an input
Entry rate	-0.011	-0.068	0.023	-0.049	2.411***	1.925***	2.905***	2.307***
	(-0.10)	(-0.73)	(0.37)	(-0.72)	(7.71)	(4.62)	(9.35)	(5.43)
Constant	0.650***	0.677***	0.717***	0.658***	5.896***	5.469***	6.288***	6.185***
	(28.62)	(37.17)	(24.96)	(22.80)	(12.16)	(13.46)	(14.71)	(20.08)
Number of observations	1427	1519	1458	1583	2069	2156	2124	2243
Number of groups	532	583	543	608	735	809	756	844
Chi-squared	132.308***	150.524***	64.885***	67.884***	211.532***	188.342***	209.823***	221.484***
Panel-level standard deviation	0.000***	0.000***	0.123***	0.120***	2.783***	1.995***	2.372***	1.209***
Standard deviation of epsilon	1.309***	0.470***	0.094***	0.101***	0.576***	0.634***	0.553***	0.559***
Rho	0.000***	0.000***	0.629***	0.588***	0.959***	0.908***	0.948***	0.824***

Notes: The results stem from estimating the system of two-stage least-squares equations (2SLS for the panel data) for each year for the effects of innovation on TE and productivity. Only the second stage IV regressions are reported. TE refers to the TFP distance to the best performing plant in the sector and ranges from 0 to 1. *t* statistics in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 6. Sales growth following innovation and productivity gains

	Product innovation output with R&D input	TE from product innovation output	Process innovation output with R&D input	TE from process innovation output
Lagged product innovation	0.053**			
	(2.96)			
Lagged process innovation			1.619***	
			(3.47)	
Lagged TE		3.147		8.591
		(1.55)		(1.00)
Lagged turnover	-0.026**	0.000	-0.045***	-0.050
	(-2.50)	(0.02)	(-3.34)	(-1.39)
Liquidity	0.025	0.001	0.029	0.128
	(0.73)	(0.01)	(0.80)	(1.01)
Age	0.001**	0.002*	0.002**	0.004
	(2.17)	(1.67)	(2.81)	(1.23)
Industry growth rate	0.263***	0.393***	0.254***	0.658*
	(4.03)	(3.86)	(3.77)	(1.66)
Other controls	included			
Const	0.085	-2.322*	0.226	-5.566
	(0.74)	(-1.68)	(1.64)	(-0.96)
Number of observations	1961	1801	2022	1919
Number of groups	676	655	698	699
Chi-squared	32**	21**	37***	7
Panel-level standard deviation	0.270**	0.000**	0.344***	0.398
Standard deviation of epsilon	0.409**	1.880**	0.423***	0.425
Rho	0.304**		0.399***	0.467

Notes: The sales growth following innovation and productivity gains are calculated conditional on firm survival. The results are from estimating the system of two -stage least-squares equations (2SLS on the panel data) for each year and relate to how innovation affects growth. Only the second stage IV regressions are reported. TE refers to the TFP distance to the best performing plant in the sector and ranges from 0 to 1. *t* statistics in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 7. The impact of innovation, productivity and growth on survival.

	R&D and survival		Product innovation and survival		Process innovation and survival		TE and survival		Labor productivity and survival		Sales growth and survival	
	R&D	Interaction with the small size dummy	Product innovations	Interaction with the small size dummy	Process innovation	Interaction with the small size dummy	TE	Interaction with the small size dummy	Labor productivity	Interaction with the small size dummy	Sales growth	Interaction with the small size dummy
R&D	0.973	0.966										
	(-0.43)	(-0.49)										
R&D x small size		0.372**										
		(-2.84)										
Product innovation			0.943*	0.953								
			(-1.83)	(-1.46)								
Product innovation x small size				0.664**								
				(-2.55)								
Process innovation					0.612	0.588						
					(-0.99)	(-0.93)						
Process innovation x small size						0.433						
						(-0.46)						
TE							0.502	0.964				
							(-0.58)	(-0.03)				
TE x small size								17.215				
								(0.86)				
Labor productivity									0.694***	0.843		
									(-4.66)	(-1.38)		
Labor productivity x small size										0.661**		
										(-2.42)		
Sales growth											0.630***	0.592***
											(-4.91)	(-4.35)
Sales growth x small size dummy												1.032
												(0.17)

Table 7. The impact of innovation, productivity and growth on survival. Continued

	R&D and survival		Product innovation and survival		Process innovation and survival		TE and survival		Labor productivity and survival		Sales growth and survival	
	R&D	Interaction with the small size dummy	Product innovations	Interaction with the small size dummy	Process innovation	Interaction with the small size dummy	TE	Interaction with the small size dummy	Labor productivity	Interaction with the small size dummy	Sales growth	Interaction with the small size dummy
Small size dummy	3.351*** (3.32)	0.381 (-1.26)	3.633*** (3.54)	1.741 (1.18)	3.455*** (3.34)	3.621** (3.18)	2.565 (0.90)	0.388 (-0.41)	1.549 (0.98)	11.149** (2.17)	1.533 (0.88)	1.494 (0.76)
Entry rate	0.000*** (-4.94)	0.000*** (-5.01)	0.000*** (-4.47)	0.000*** (-4.37)	0.000*** (-4.78)	0.000*** (-4.79)	0.000** (-2.18)	0.000** (-2.14)	0.000*** (-4.07)	0.000*** (-4.01)	0.000*** (-4.46)	0.000*** (-4.43)
Controls	Controls for firm liquidity, ownership, age, specialization, market share and host city size are included											
Number of observations	6192	6192	5606	5606	5904	5904	5018	5018	6664	6664	5699	5699
Number of subjects	6170	6170	5584	5584	5882	5882	4996	4996	6642	6642	5677	5677

Note: All estimations use the Cox proportional hazard model. Regression coefficients are the hazard ratio (exponentiated coefficients). Z statistics are reported in parentheses beneath the coefficients. Robust standard errors are used. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Figures

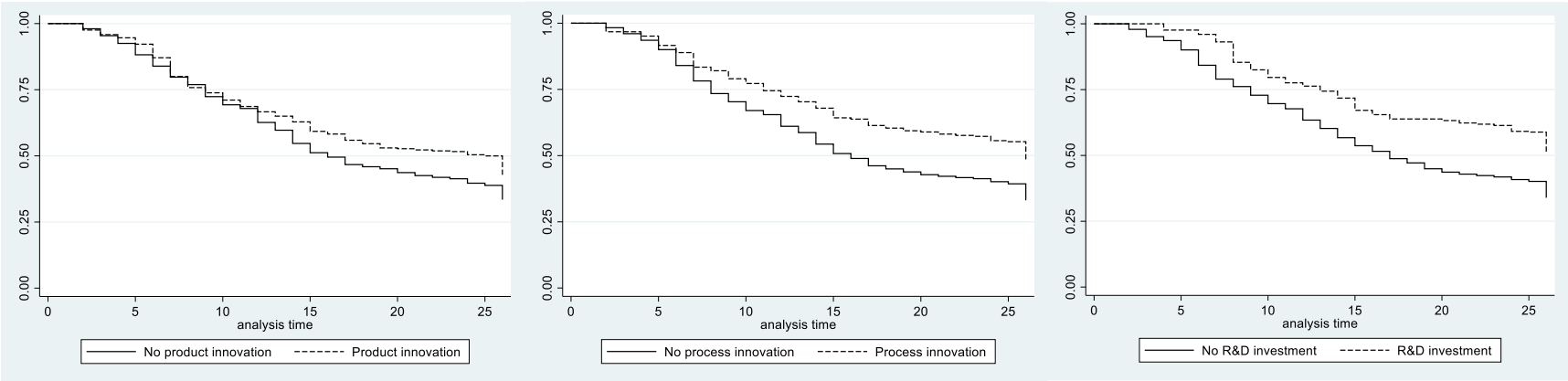

Figure 1. Kaplan-Meier survival by type of innovation.
Note: The horizontal axis shows the number of survival years, starting from 1991 and the vertical axis displays the Kaplan-Meier survival estimates. Failure is defined as exit of the plant from the market. All of the data are weighted. Product innovations, process innovations, and R&D spenders in this figure are defined by the dummies.

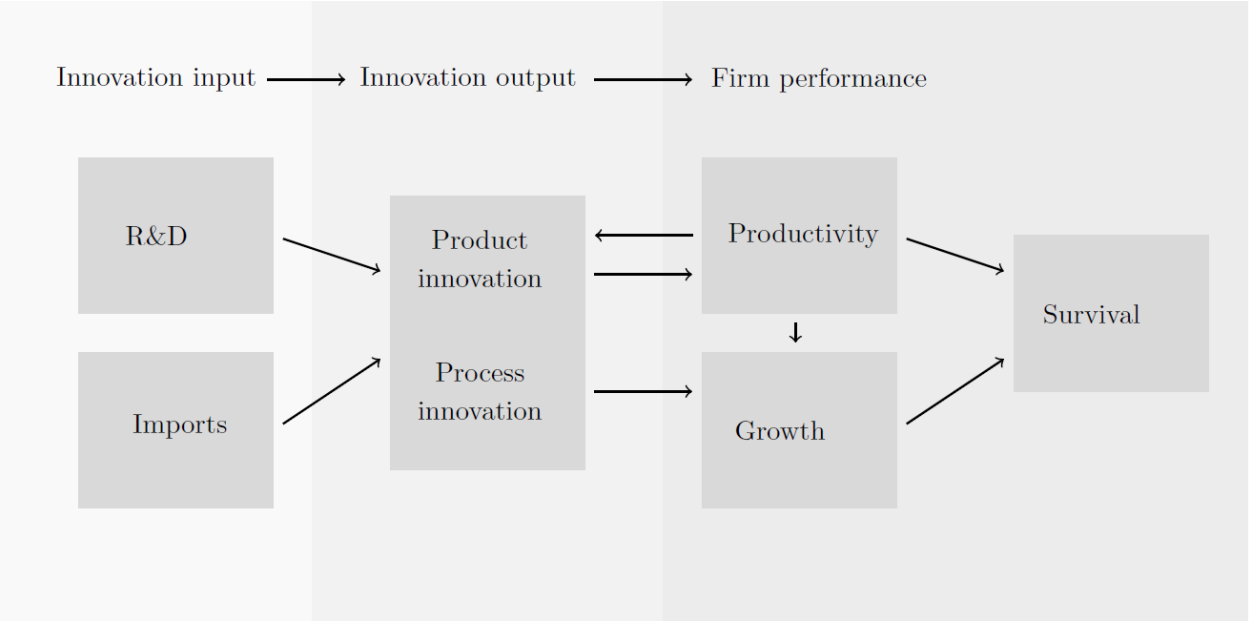

Figure 2. The research model applied in the study