The Impact of Innovation on Productivity: Profitability and Technical Efficiency

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Abstract: The productivity measures used so far in the innovation literature reflect firm performance, which confounds profitability and technical efficiency. Nevertheless, the distinction between the two is crucial. We propose a decomposition model to improve our understanding of how firms profit from innovation. We apply this model using a unique dataset with product level data on prices and quantities next to information on innovation activities and traditional firm performance measures. We differentiate between demand driven and cost driven innovation and find that firms appropriate profits of both types of innovation through a markup premium, but only firms that do cost driven innovation also have a technical efficiency premium.

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1. Introduction

Understanding how returns of innovation can be appropriated is crucial for managers and policy makers. For managers it is important to understand how different types of innovation can have disparate effects on the revenues and costs of their activities (Geroski, Machin and Van Reenen, 1993). For policy makers, it is of paramount importance to understand how different types of innovation relate to markup and productivity growth (Hall, 2011; Jaumandreu and Lin, 2018). The last decades, we saw an increase in market power and economic inequality (De Loecker, Eeckhout and Unger, 2018) that coincided with low productivity growth (Syverson, 2017). In light of these trends, Van Reenen (2018) discusses several macro-phenomena related to innovation dynamics. Crouzet and Eberly (2018) suggest that innovations in business processes, brand and intellectual property are an important enabler of the rise of superstar firms and the increase in industry concentration. We contribute to this debate by modeling and empirically estimating how firms appropriate productivity and markup returns of innovation. This paper shows that, in order to do so, it is not only important to distinguish between different types of innovation but that it is also crucial to look at the adequate measure of productivity.

It is commonly advocated that innovating firms have a productivity premium.[1] However, it is not obvious whether innovation induces productivity changes through demand or cost effects.[2] Innovation can affect the demand for products, which is most likely the aim of product and marketing innovation, or decrease the costs of production, which is most likely the purpose of process and organizational innovation. Without using price and quantities data to estimate productivity, it is not possible to distinguish between demand and cost effects when relating innovation to productivity (Griliches and Mairesse, 1995; Griliches, 1998). Nevertheless, this distinction is important for deriving the impact of innovation on welfare (Hall, 2011).

The lack of adequate data to uncover the exact mechanism by which innovation affects productivity restricted researchers so far to impose a model on market conduct or a setting where they need to assume that input and output markets are perfectly competitive. Both solutions are imperfect in settings where firms are heterogeneous, because then the inability to distinguish between price and quantity effects results in biased estimates of returns on innovation. For example, product innovation typically results in some form of market power in the output market because of a first mover advantage in new or improved products or services. This allows firms to sell above competitive prices in a monopolistic setting (Lieberman and Montgomery, 1988).

[1] See Doraszelski and Jaumandreu (2013), Bilir and Morales (2016) and Peters, Roberts, Vuong and Fryges (2017) for recent work and Mohnen and Hall (2013) for a survey paper of the innovation and productivity literature. See appendix B for a graphical illustration of the heterogeneity in earlier studies.

[2] Notable exceptions are Van Leeuwen and Klomp (2006), Petrin and Warzynski (2011), Cassiman and Vanormelingen (2013), Jaumandreu and Mairesse (2010, 2017) and Jaumandreu and Lin (2018) who each in a different way advance our understanding of how innovation affects productivity. Yet, a comprehensive framework to disentangle the puzzle is still missing, which is what we aim to contribute with this paper.

Using an industry wide deflator in estimating the production function would underestimate the output price of these firms. As a consequence, the measured impact of product innovation on productivity could in fact simply reflect price effects. For process innovation the opposite is true, such innovation practices are typically undertaken to reduce the cost per unit of production. If the firm passes its cost savings through (Amiti, Itskhoki and Konings, 2014), this would result in the industry wide deflator overestimating the output price. The effect of process innovation on productivity could thus be biased downwards with labor productivity or revenue productivity measures. These examples illustrate the need for disentangling traditional productivity measures to better understand how innovation affects firm performance.

The aim of this paper is twofold. First, we relate innovation to productivity measures that do not confound price and quantity effects. We will reconcile our findings with the earlier innovation economics literature, which is characterized by large heterogeneity in productivity returns from innovation. Second, we propose a decomposition model to disentangle how firms appropriate profits from innovation. This allows us to show how the effect of innovation on productivity adds up with the effect of innovation on other micro-determinants of firm performance to the effect of innovation on profitability.

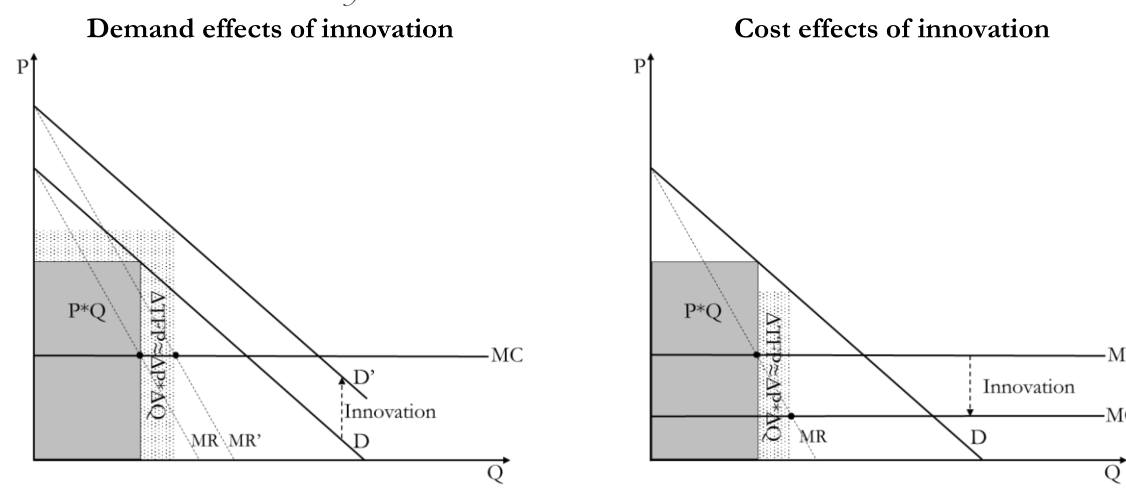
Comparing innovating to non-innovating firms, we find that demand driven innovation and cost driven innovation come with similar profit premiums through higher markups. However, only firms that do cost driven innovation also have lower marginal costs and a true technical efficiency premium. Furthermore, we find that for firms who do demand innovation, or both demand and cost innovation, output prices are an important determinant of revenue productivity differences. This suggests prices are an important explanation for the large heterogeneity in findings of productivity returns from innovation in earlier studies. Furthermore, the insights in this paper are important for deriving welfare implications from innovation.

The remainder of the paper is organized as follows. Section 2 provides some theoretical background on productivity and innovation. Section 3 shows how profits can be decomposed into production costs, markups, marginal costs, technical efficiency and composite output and how we relate innovation to each of these components. Section 4 presents the dataset and the results are presented in section 5. Finally, section 6 concludes the paper.

2. Theoretical Framework

The concept of productivity dates back to the work of Solow (1957), who defined total factor productivity (TFP) growth as rising output with constant capital and labor input. So in theory, productivity reflects output per unit of composite input, taking into account the production technology relating inputs to output. In practice, output is typically measured in value added or revenues, deflated by a sector wide price deflator. Unless one is willing to assume that firms produce homogeneous products and are subject to perfect competition in both input and output markets, productivity is a revenue residual (TFPR) that confounds true technical efficiency or physical productivity (TFPQ) with market power both in the input and output markets (Griliches and Mairesse, 1995; Klette and Griliches, 1996). Recently, advances were made in the productivity literature to recognize these confounding factors in estimating production functions. We refer to De Loecker and Goldberg (2014) and Haltiwanger (2016) for a theoretical overview of different TFP measures and how discerning between TFPR and TFPQ can push the literature to a richer understanding of firm dynamics.

Figure 1: Innovation and Productivity



Notes: The figures show the expected impact of demand and cost innovation under monopoly. The insights also hold more generally under monopolistic competition and with different demand and supply elasticities.

Figure 1 illustrates how the innovation economics literature would benefit from disentangling TFP. TFPR is the part of revenues (P*Q) that cannot be attributed to input factors and technology. However, without having data on prices and quantities, a model with ΔTFPR as dependent variable and innovation as an independent variable obfuscates the exact mechanism. Indeed, while ΔTFPR is positively affected by innovation in both panels of figure 1, it is associated with a positive price effect (ΔP) of innovation in the left panel and a negative price effect in the right panel. As a result, it is e.g. hard to derive welfare implications from revenue productivity measures (Hall, 2011) because we cannot dissociate between (i) innovation resulting in market power or (ii) innovation leading to an increase in the efficiency of production, while this are two very different things. If innovation results in price increases, this is only welfare enhancing to the extent that such price increases reflect quality improvements.

We follow the OSLO manual (2005) and include four types of innovation: product (new goods or services or significant improvements in existing ones), process (changes in production or delivery methods), organizational (changes in business practices, workplace organizations or external relations) and marketing innovation (changes in product design, packaging, placement, promotion or pricing). We refer to appendix C.1 for further information and definitions. Based on principle component analysis (see section 4 and appendix B.2), we distinguish between demand innovation, i.e. product and marketing innovation, and cost innovation, i.e. process and organizational innovation.

The literature finds positive productivity returns of product innovation (see figure A-1 in appendix B). Yet, one might expect that the introduction of a new good or service rather decreases firm efficiency as this type of innovation oftentimes requires setting up new production lines or modifying existing production processes. While it is not obvious how such increases in organizational complexity could result in higher firm efficiency, it is more plausible that product innovations result in demand from new markets and higher willingness to pay of consumers (Jaumandreu and Mairesse, 2017; Acemoglu and Linn, 2004). The same holds for marketing innovation, which one would also expect to impact productivity as described in the left panel of figure 1. This raises the question whether the earlier consensus on productivity returns of product and marketing innovation is driven by a price effect and whether product innovation has any effect on firm efficiency at all.

The results on the relation between process innovation and productivity in prior literature are mixed (see figure A-2 in appendix B). Hall (2011) argues this is likely due to mismeasurement of productivity. Indeed, one would expect that introducing new methods of production, improved logistics and distribution systems or new process support systems would result in higher firm efficiency. The same holds for organizational innovation. If cost innovation is expected to increase productivity, why do some studies find the opposite? A potential explanation is that process innovators set lower prices, as in the right panel of figure 1. If firm efficiency (TFPQ) increases but output prices (P) decrease, the net effect on TFPR is not clear ex ante. The expected opposing effects of different types of innovation on output prices, i.e. product innovation to be associated with high prices and process innovation with low prices, could also explain why studies that include both product and process innovation often report positive returns of product innovation and negative returns of process innovation.

So far, there is mixed evidence on the complementarities between different types of innovation in explaining profit and productivity differentials between firms. The reason for the lack of evidence on this question could be the existence of collinearity issues when regressing traditional productivity measures on multiple innovation indicators (Hall, 2011). Cassiman and Vanormelingen (2013) found no evidence on complementary effects between product and process innovation. On the other hand, Carboni and Russu (2018) show there is interdependence in the decision to engage in product, process and organizational innovation. Furthermore, Mothe et al. (2015) and Polder et al. (2010) find complementary effects of product, process and organizational innovation on firm performance.

3. Empirical framework

In order to investigate how firms appropriate profits from innovation, we propose a decomposition of revenues and costs, which together add up to profits. Our measure of profitability is the firm's price to average cost margin, or when multiplied with quantities, the ratio of revenues to costs:[3]

$$\Pi_{ijt} = \frac{P_{ijt} * Q_{ijt}}{AC_{ijt} * Q_{ijt}} \tag{1}$$

Where the subscripts i, j and t refer to product, firm and year. P_{ijt} is the price a firm charges for its product, Q_{ijt} is the quantity produced and AC_{ijt} is the average cost of the product. $P_{ijt} * Q_{ijt}$ is the revenue a firm realizes from selling the product, and $AC_{ijt} * Q_{ijt}$ is the cost of the composite input associated to producing the product. We further decompose revenues and costs by taking logs of equation (1):

$$\begin{aligned} \ln(P_{ijt}Q_{ijt}) &= \ln(P_{ijt}) + \ln(Q_{ijt}) = p_{ijt} + q_{ijt} \\ \ln(AC_{ijt}Q_{ijt}) &= \ln(AC_{ijt}) + \ln(Q_{ijt}) = ac_{ijt} + q_{ijt} \end{aligned} \tag{2}$$

Now assume that the production process of a firm can be described by a Cobb Douglas production function of the form $Q = A * L^{\beta_l} * K^{\beta_k} * M^{\beta_m}$.[4] Furthermore, we assume monopolistic competition such that firms can charge a markup, which we define as the ratio of price over marginal cost: $\mu = \frac{P}{MC}$ as in De Loecker and Warzynski (2012). Taking logs of the production function and markup equation allow us to rewrite prices and quantities from equation (2) as follows:

$$\begin{aligned} &\text{(i)} \quad p_{ijt} = \mu_{ijt} + mc_{ijt} \\ &\text{(ii)} \quad q_{ijt} = a_{ijt} + \beta_l * l_{ijt} + \beta_k * k_{ijt} + \beta_m * m_{ijt} = a_{ijt} + f(x_{ijt}) \end{aligned} \tag{3}$$

This straightforward decomposition provides us with a rich set of firm performance determinants. The revenue that a firm realizes on a product is decomposed into the price of the product and the quantity sold. The price is further decomposed into the markup (μ_{ijt}) and the marginal cost (mc_{ijt}) associated with the production of the product. The quantity is decomposed into the part of production that can be attributed to the input factors $f(x_{ijt})$ and the part of production attributed to the efficiency of the firm in producing the product, denoted by a_{ijt}. It is this last component of firm performance that is commonly known as 'Total Factor Productivity (TFP)', i.e. the part of production that cannot be explained by the traditional input factors labor, capital and materials. We are explicit in our notation of writing a_{ijt} as residual *quantities*, which is an indication of how this paper will contribute to the literature. The innovation economics literature so far largely relied on production functions

[3] This measure of profitability is very similar to the one used in Jaumandreu and Lin (2018).
[4] For the sake of simplicity, we develop the model based on the Cobb Douglas production function, which is a first order approximation to any production function. In practice, we will allow for a more flexible production technology, using the Transcendental Logarithmic production function (Christensen, Jorgenson and Lawrence, 1973).

with *revenues* as dependent variable, in logs $P + Q = f(x) + \omega$.[5] Comparing this with equation (3) shows that $\omega = a + p$, which shows how earlier literature confounded productivity with prices and thus also with market power (~markups).[6] To see how each of these firm performance measures relate to innovation, we using the following set of regressions:

$$\Pi_{ijt}\begin{cases} AC_{ijt}Q_{ijt}\begin{cases} ac_{ijt} &= \beta_0 + \beta_{Inn}^{ac} * Inn_{jt} + W_{jt} + \epsilon_{ijt} \\ q\begin{cases} \widehat{tfpq}_{ijt} = \beta_0 + \beta_{Inn}^{tfpq} * Inn_{jt} + W_{jt} + \epsilon_{ijt} \\ \hat{f}(x_{ijt}) = \beta_0 + \beta_{Inn}^{f_{x_{ijt}}} * Inn_{jt} + W_{jt} + \epsilon_{ijt} \end{cases} \end{cases} \\ P_{ijt}Q_{ijt}\begin{cases} p\begin{cases} \hat{\mu}_{ijt} &= \beta_0 + \beta_{Inn}^{\mu} * Inn_{jt} + W_{jt} + \epsilon_{ijt} \\ \widehat{mc}_{ijt} &= \beta_0 + \beta_{Inn}^{mc} * Inn_{jt} + W_{jt} + \epsilon_{ijt} \end{cases} \end{cases} \end{cases} \tag{4}$$

The dependent variable is always the natural logarithm and the innovation measures are dummies such that the coefficients can be roughly interpreted as the percentage difference in the firm performance determinant as a result of engaging in the innovation activity. The advantage of the way we set up the model, is that the coefficients of the regressions in (4) can simply be added up to gauge the total effect of innovation. This is because the regressions have identical sets of explanatory variables while the dependent variables all originate from log-transformations of the firm performance measure presented in equation (1). For example, $\beta^{tfpq} + \beta^{f_x}$ shows the effect of innovation on quantity sold, $\beta^{\mu} + \beta^{mc}$ the effect of innovation on price, $\beta^{\mu} + \beta^{mc} + \beta^{tfpq} + \beta^{f_x}$ the effect of innovation on revenues, $\beta^{ac} + \beta^{tfpq} + \beta^{f_x}$ the effect of innovation on costs and $\beta^{\mu} + \beta^{mc} - \beta^{ac}$ the effect of innovation on the ratio of revenues to costs. Altogether, the regressions in (4) allow us to decompose how firms appropriate profits from innovation.

Before taking equation (4) to the data, we need to compute the various firm performance measures introduced in the decomposition model. While prices, quantities and the costs of production are readily available in the data, we need to estimate *quantity* production functions to obtain estimates for TFPQ (a_{ijt}), the markup (μ_{ijt}) and the marginal cost (mc_{ijt}). To obtain unbiased estimates for β_l, β_k and β_m, we use and extend the control function approach of Olley and Pakes (1996) and estimate it as in Wooldridge (2009) to account for simultaneity between input choices, productivity and innovation. We control for input price bias as in De Loecker et al.

[5] To the best of our knowledge, no study so far used data on production quantities in the innovation economics literature. Instead, TFP(R) is usually obtained as a revenue residual from regressing a firm's revenues (y) on the production factors, i.e. $y = tfpr + \beta_l * l_{it} + \beta_k * k_{it} + \beta_m * m_{it}$. The factor elasticities $(\beta_l, \beta_k, \beta_m)$ then reflect both factor elasticities and demand parameters. Actually, most studies on innovation and productivity restrict to the relation between innovation and labor productivity, which not only mixes up demand and true productivity, but is furthermore subject to mismeasurement of productivity by ignoring the production factor capital.

[6] We follow Syverson et al. (2008) and Haltiwanger (2016) and define a firm's revenue productivity (TFPR) as $tfpq_{ijt} + p_{ijt}$. As output prices are typically not available, researchers so far largely proceeded with using price deflators to correct for output price biases in productivity. As documented by De Loecker and Goldberg (2014), this solution ignores substantial heterogeneity from the firm's pricing power in input and output markets.

(2016) and allow for an endogenous evolution of productivity depending on the innovation status of the firm as in Amiti and Konings (2007), De Loecker (2013) and Doraszelski and Jaumandreu (2013). We estimate markups as in De Loecker and Warzynski (2012) and Cassiman and Vanormelingen (2013). For a more rigorous description of the estimation procedure, we refer to appendix A.

With all firm performance measures obtained from the data or estimated, we use equation (4) to relate each of them to mutually exclusive groups of innovators (see section 5) to show how different types of innovation are associated to differences in firm performance. While we account for possible endogeneity channels in estimating the production function, this does not guarantee causality in equation (4). The purpose of decomposition exercises is typically to understand how certain effects come about. In this paper, we are interested in understanding how the effect of innovation on revenues and costs can be explained. By constructing the decomposition as a regression model, we are furthermore able to say something about the uncertainty of the channels. Notwithstanding, it is important to mention that endogeneity can arise because of omitted variables that are related to both the innovation and the firm performance variables of interest, e.g. competition (see Schumpeter (1942), Arrow (1962) and Aghion (2005)) and export status (see Cassiman and Golovko (2011) and Cassiman, Golovko and Martínez-Ros (2010)). Results could also be subject to simultaneity when firms with better firm performance self-select into innovation. To minimize potential bias in the coefficients of equation (4), we include a set of control variables represented by vector W_{jt}, which contains: the size of the product portfolio, the sales share of the product in firm sales, the export status, a self-reported measure of competition the firm faces, a firm size indicator, firm age and industry and year fixed effects.[7] Yet, we want to stress that we are not interpreting the effects as causal, but, to our knowledge, the insights we derive have not been documented and we see this as an important set of results in order to understand how firms appropriate returns of innovation.

[7] We experimented with instrumental variables, but it is hard to find instrumental variables for *both* cost and demand innovation that plausibly meet the exclusion restriction.

4. Data

We rely on three different datasets that we merge based on the firm's unique VAT number. The first dataset we use, is the Belgian Community Innovation Survey (henceforth, CIS) to obtain information on innovation practices at the firm level.[8] More particularly, we use the CIS 2005, CIS 2007, CIS 2009 and CIS 2011 waves. For a discussion on the usefulness of this database for measuring innovation practices at the firm level, we refer to Mairesse and Mohnen (2010). The innovation definitions employed by the CIS are based on the OSLO manual (OECD, 1992, 1996, 2005). For this paper, we are mainly interested in the questions on product, process, organizational and marketing innovation. Using the information on these questions, the CIS allows us to construct a dummy variables for each type of innovation.[9] Furthermore, we also construct a measure for the competition the firm faces and the export status of the firm from this dataset.[10] More information and an overview of the relevant CIS questions can be found in appendix C.1.

The second dataset is the survey on Products of the European Community (henceforth, ProdCom) of Belgium. This dataset provides highly detailed product level data for mining, quarrying and manufacturing firms.[11] We know for each firm the 8-digit product codes in which it is active, but more importantly the dataset also contains for each of these product codes information on the quantity sold and the associated revenue. This allows us to compute unit prices across the firm's product portfolio. Finally, the first four digits of the 8-digit ProdCom product code refer to the industry classification of the product. We use this information to assign industry codes to each product, which is especially useful for the treatment of multiproduct firms and provides us a narrow and more qualitative industry classification than could be derived from annual accounts data. See appendix C.2 for more information on the content and structure of the ProdCom dataset.

Next to information on innovation practices (CIS), prices and quantities (ProdCom), we obtain firm level data on production inputs from annual accounts data of the National Bank of Belgium. This dataset provides us with the additional variables needed for estimating production functions. More specifically, as a measure for labor input, we observe the number of full time employees and hours worked. To measure capital inputs, we use the reported tangible fixed assets. Furthermore, this dataset contains information on turnover, intermediate inputs

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[8] The CIS data is an established data source for empirical firm level analyses on innovation, including research on the link between innovation and firm performance, e.g. Raymond, Mairesse, Mohnen and Palm (2015). See appendix C.1 for more information about the CIS.

[9] In practice, the innovation dummy is set equal to one if a firm answers "yes" on one of the relevant questions. For robustness checks purposes, we also experimented with innovation intensity measures, based on the number of relevant questions that are answered with "yes". This did not change the qualitative findings.

[10] The measure on competition and export was not available for all firms and all CIS waves. When missing, we replaced the competition measure by the average competition measure of more aggregate levels – either at the 3 or 2 digit level.

[11] This survey is mandatory for each industrial firm that employs at least 20 persons or has a revenue of at least 3.928.137 euro in the current or past year. For each firm, this dataset provides production statistics for all 8-digit product codes in which the firm is active. See appendix C.2 for an illustration of the level of detail. We abstract from potential product heterogeneity within 8-digit codes.

use, investments and depreciation. Additional deflators for input and output variables were obtained from Eurostat.

To estimate the production functions, we can use the full panel by treating the innovation measures as state variables. For estimating the decomposition (equation 4), we collapse the data to the product-CIS-wave level because this is the level at which there is variation in the variables of interest, which are the innovation dummies. We do not collapse our data to the firm level, because this would entail problems for firms that produce products that are measured in different units. Hence we make the implicit assumption that, when firms report innovation, they take place for each product, which is an implicit assumption in the earlier literature as well. The final sample for the decomposition model is constructed from the intersection between our three data sources, which results in a sample of 7,213 observations about 1,449 products produced by 1,495 firms.

Tables 1-3 show summary statistics of the most relevant variables from each data source. All tables are for the final sample that we obtain after merging the CIS, ProdCom and annual accounts data. Table 1 shows which innovation activities are reported most frequently in our sample of 7,213 observations.

Table 1: Summary statistics CIS data - frequency of innovation activities

Frequency table			No innovation	**Process Innovation**			
			Demand driven	0		1	
			Cost driven	**Organizational Innovation**		**Organizational Innovation**	
			Both	0	1	0	1
Product Innovation	0	**Marketing Innovation**	0	1,646	166	338	285
			1	134	81	72	138
	1	**Marketing Innovation**	0	491	189	679	786
			1	224	233	362	1,389

Notes: The frequency of each possible combination of innovation activities in the final sample used in the decomposition.

About 20% of our sample reports no innovation activities. Another 20% of our sample reports doing all types of innovation. Furthermore, some combinations seem to occur more than others, but in general the bulk of firms report doing multiple types of innovation. This raises the question on complementarities between different combinations of innovative activities. In total, there are 16 different innovation combinations possible. Including all these combinations in equation (4) would result in identification problems because of a low number of observations per combination and multi-collinearity. Therefore, we try to obtain a meaningful reduction of the dimensionality of the possible combinations presented in table 1. One way to do this, is performing a principle component analysis on the different types of innovation. In appendix B we show the results for such an analysis, both for the aggregate innovation categories in table 1 as for all questions of the CIS separately. The principle component analysis suggests to retain two factors out of the four innovation categories from table 1. The first factor loads high on all types of innovation, the second factor loads negatively on product and marketing innovation and positive on process and organizational innovation. This suggests a common factor 'innovation' and another factor which reflects 'demand versus cost innovation'.[12] This in line with our prior expectations that (i) product and marketing innovation go together and (ii) process and organizational innovation go together. As sketched in figure 1, product and marketing innovation are expected to create new demand from e.g. introducing new varieties or quality upgrading of existing products. Process and organizational innovation are expected to decrease costs, e.g. by improving the efficiency of current production processes or introducing new production methods. In the results, we will thus compare four types of firms: those that do not innovate, those that do exclusively demand driven innovation, those that do exclusively cost driven innovation and those that do both types of innovation.

Table 2 shows for the same sample summary statistics on annual accounts variables. There is large heterogeneity in firm size and sales across our sample. Although the sample is limited to Belgian firms, the range of our variables is similar to studies based on CIS data of Germany (Peters et al., 2017), France, Spain and the U.K. (Harrison, Jaumandreu, Mairesse and Peters, 2014).

Table 2: Summary statistics annual accounts data (in 2005 euros)

Variable	*Mean*	*Standard Deviation*	*p25*	*p50*	*p75*
Turnover (thousands)	247,062,554	762,976,302	5,847,046	21,330,253	123,303,366
Added Value (thousands)	64,002,205	201,489,302	1,797,451	6,336,619	30,169,181
Employment	430	884	32	87	372
Labor Productivity	85,280	57,262	51,200	69,898	100,253
Material expenditures (thousands)	194,811,143	609,524,574	4,192,493	15,341,882	94,449,339
Tangible Fixed Assets (thousands)	30,006,043	90,405,708	779,023	3,183,326	14,203,823
Number of products	9	15	2	4	10

Notes: Summary statistics on prices and quantities are omitted because they are not informative across products.

The average firm employs 430 employees, has a capital stock of 30million EUR and produces 9 products. The median summary statistics are considerable lower than the mean values, indicating that the upper percentiles of the distribution consists of rather large firms. As the 25th percentile shows, there are also relatively small firms in our sample.

[12] The principal component analysis based on all CIS questions gives similar results. There is one common component that loads positive on all questions, which can be labeled as 'innovation'. According to the eigenvalue statistics, two other components should be retained: one that loads only negative on organizational innovation and one that loads low or negative on both process and organizational innovation, while product and marketing innovation load positively on both components.

Finally, table 3 presents summary statistics from the Prodcom dataset for the sample of firms that we also have data on innovation practices from the CIS and firm performance from the annual accounts.

Table 3: Summary statistics ProdCom data in our sample

Industry	Share of Sample	# Products	# Firms	# Single Product	# Multi product
10 - 12: Food, Beverages and Tobacco	15%	187	277	82	195
13 - 15: Textiles, Apparel and Leather	4%	181	147	57	90
16 - 18: Wood, Paper and Printing	3%	73	97	47	50
20 - 21: Chemicals and Pharma	29%	291	130	52	78
22 - 23: Rubber and Non-Metallic Minerals	7%	163	235	138	97
24 - 25: Metals	15%	172	255	165	90
26 - 28: Computers, Electrical and Machinery	13%	287	232	137	95
29 - 30: Vehicles and Transport Equipment	13%	49	46	32	14
31 - 33: Furniture, Other Manuf. and Repair	2%	46	76	38	38
Total	100%	1449	1495	748	747

Notes: The share of sample refers to the turnover of products in the industry to total turnover in the sample. This is not the full ProdCom sample, it is the part of the sample for which all information is available to apply the decomposition.

The food and beverages, chemicals and metals industries have the largest share in turnover. Furthermore, both the computers, electrical equipment and machinery industry and the chemicals industries produce a wide variety of products. Our final sample consists of 1,495 firms that altogether produce 1,449 different products. We have 748 single product firms and 747 multi product firms in our sample. The number of multi product firms largely exceeds the number of single product firms in food and beverages industries; while there are many single product firms in rubber, metals and computer industries.

5. Results

We first show results from the quantity production function estimation. Then we discuss how innovation relates to revenues and costs and present the profit decomposition that we designated in section 3.1.

Table 4: Median output elasticities and markups (by sector)

Industry	β_l	β_k	β_m	RTS	Markup		
					Median	P10	P90
10 - 12: Food, Beverages & Tobacco	0.18	0.02	0.80	1.01	1.07	0.91	1.35
13 - 15: Textiles, Apparel & Leather	0.17	0.06	0.74	1.00	1.11	0.91	1.33
16 - 18: Wood, Paper & Printing	0.26	0.02	0.69	0.99	0.93	0.81	1.09
20 - 21: Chemicals & Pharma	0.13	0.03	0.85	1.01	1.10	0.89	1.25
22 - 23: Rubber & Non-Metallic Minerals	0.18	0.04	0.79	1.00	1.09	0.95	1.33
24 - 25: Metals	0.25	0.02	0.76	1.00	1.12	0.88	1.38
26 - 28: Computers, Electrical & Machinery	0.32	0.01	0.58	1.00	0.88	0.59	1.19
29 - 30: Vehicles & Transport Equipment	0.20	0.07	0.84	1.10	1.22	0.95	3.08
31 - 33: Furniture, Other Manuf. & Repair	0.17	0.06	0.85	1.02	1.23	1.01	2.60
Average	0.19	0.03	0.78	1.00	1.08	0.84	1.32

Notes: The first three columns show the median estimated output elasticities from the quantity Translog production function for each industry. Column 4 reports the median returns to scale. Columns 5-7 report the median markup and the markup at the 10^{th} and 90^{th} percentile per industry.

The production function is estimated by industry and includes controls for potential input price bias and simultaneity bias from unobserved productivity while allowing an endogenous productivity evolution. A more elaborate overview of the estimation procedure can be found in appendix A. Our estimates suggest constant returns to scale. As a result, the marginal cost is close to the average cost of production. This will result in the relation between innovation and marginal costs being very similar to the relation between average costs and innovation. The labor and materials coefficients are close to theoretical expectations, the capital coefficient is rather low.[13] The average median markup across all sectors is 1.08, indicating that the median firm sets on average a price for its products that is 8% above marginal cost. There is dispersion in markups within industries. The markup of products at the 10^{th} percentile of the markup distribution is on average equal to 0.84, which indicates that some products are sold below their marginal cost. The markup of products at the 90^{th} of the markup distribution is on average equal to 1.32, which indicates that those products are sold 32% above their marginal cost.

[13] This is a common issue in the Wooldridge (2009) version of the Olley and Pakes (1996) approach because the polynomial in lagged investment demand and lagged capital to proxy for unobserved productivity is included in a one-step GMM estimator and these variables are typically highly correlated with the current capital stock, thereby lowering the coefficient on the current capital stock variable.

5.1 The return of innovation

As a first step in disentangling the relation between innovation and firm performance, we pool all types of innovation and run the regressions from equation (4) with as baseline group the non-innovating firms. In order to guarantee that the coefficients across the different levels of the decomposition add up, all regressions include the same set of control variables: firm age, export status, a self-reported measure of competition, the size of the product portfolio measured by the number of products, the sales share of the product in the firm, a firm size indicator, year dummies and industry dummies. All standard errors are bootstrapped, the significance levels of all estimates in the paper are also robust to estimating equation (4) as seemingly unrelated regressions and to using robust standard errors instead of bootstrapped standard errors.

Table 5: Firm performance decomposition I

Dependent variable	Revenues $(p+q)$ & Cost of Production $(ac+q)$			Profit Index $(p-ac)$
	Price(p)	Quantity (q)	Average cost (ac)	
Innovation	0.096 (0.064)	-0.003 (0.085)	0.083 (0.064)	0.013*** (0.005)
R^2	0.613	0.608	0.611	0.063
# observations	7,213	7,213	7,213	7,213

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Table 5 shows how innovation is associated to revenues, costs and profits. By construction, the coefficients of the price and quantity regressions add up to the effect of innovation on revenues while the coefficients of the quantity and average cost regressions add up to the effect of innovation on costs. The difference between the revenue and costs coefficients shows the innovator's profit premium, defined as the ratio of revenues to costs.

Innovating firms charge on average around 10% higher prices than non-innovating firms, although this difference is not significant.[14] Adding up the price and quantity effects results in a coefficient of 0.094, indicating that revenues are about 10% higher in innovating firms, mainly as a result of higher prices in innovating firms. A separate regression shows this effect to be marginally significant. This is in line with the summary statistics in table A-6 of appendix B. The same exercise can be made to derive the effect of innovation on costs. Innovating firms have about 9% higher average costs than non-innovating firms. Adding up the quantity and average cost coefficients, we find that innovating firms have on average about 8% higher total costs than non-innovating firms. Yet a separate regression shows this difference not to be significant. Finally, by adding up the coefficients from the revenue components with the cost components, we obtain an estimate for the difference in profitability between innovating and non-innovating firms. We find that innovating firms have on average a 1.3% higher profit index than non-innovating firms.

[14] The precise effect of innovation on prices is obtained from $100 * \left[e^{(\beta_{Inn}^{p})} - 1\right] = 100 * \left[e^{(0.096)} - 1\right] = 10.08\%$. In the remainder of the paper, we will always report the precise effects, which can thus slightly deviate from the coefficients in the table.

Prices and quantities can, as delineated in the decomposition in section 3, be split into markups, marginal costs, technical efficiency and composite output. Table 6 shows the results of regressing each of these firm performance determinants on innovation.

Table 6: Firm performance decomposition II

Dependent variable	Revenues $(p+q)$ & Cost of production $(ac+q)$					
	Price $(p=\mu+mc)$		Quantity $(q=tfpq+f(x))$		Average cost (ac)	Profit Index $(p-ac)$
	Markup (μ)	Marginal cost (mc)	Physical Productivity $(tfpq)$	Composite Output $f(x)$		
Innovation	0.023*** (0.007)	0.073 (0.065)	0.077 (0.076)	-0.079 (0.073)	0.083 (0.064)	0.013*** (0.005)
R^2	0.312	0.616	0.577	0.544	0.611	0.063
# observations	7,213	7,213	7,213	7,213	7,213	7,213

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Table 6 shows how the price coefficient from table 5 comes about. Innovating firms have a markup premium of 2.3% and on average 7.5% higher marginal costs than non-innovators. While the markup premium is very precisely estimated, there is a lot of heterogeneity in the marginal cost differences between innovators and non-innovators, which explains why the total effect of innovation on price was imprecisely estimated in table 5. The finding of higher markups in innovating firms is in line with Cassiman and Vanormelingen (2013) and Jaumandreu and Lin (2018).

In table 5 we found that there are hardly any difference in the production quantities between innovating and non-innovating firms. Table 6 shows that, on average, innovating firms have about 8% higher firm efficiency but produce about 8% less with their traditional input factors. These estimates are not significant and clearly hide a lot of heterogeneity, which will become apparent further in this paper when we differentiate between demand driven and cost driven innovation.

An interesting exercise on table 6 is to add up the coefficients on 'physical productivity' and 'price', since these two add up to the effect on revenue productivity, which is what earlier studies in the innovation literature reported. As explicated, the earlier innovation literature relied, to the best of our knowledge, so far largely on revenue production functions, in which basically revenues are regressed on production inputs.[15] The consequence is that the revenue residual, which is what the literature calls TFP and we label as TFPR, confounds demand and technical efficiency; basically $TFPR = TFPQ * P$, or in logs: $tfpr = tfpq + p$. The results of this exercise are shown in table 7.

[15] Exceptions of papers that either use richer data or impose additional structure are Petrin and Warzynski (2011), Cassiman and Vanormelingen (2013), Jaumandreu and Mairesse (2010, 2016) and Jaumandreu and Lin (2018).

Table 7: TFPR and TFPQ

Dependent variable	Physical Productivity ($tfpq$)	Price (p)	Revenue Productivity ($tfpr$)
Innovation	0.077	0.096	0.174***
	(0.076)	(0.064)	(0.0507)
R^2	0.577	0.613	0.36
# observations	7,213	7,213	7,213

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Consistent with earlier literature, we find a positive association between innovation and revenue productivity. Adding up the coefficients of the second and third column shows that innovating firms have a strongly significant revenue productivity premium of about 19%. Apart from a precisely estimated markup premium in innovating firms, the analysis so far learns that there is a lot of underlying heterogeneity in how innovation relates to different aspects of revenue productivity as the confidence intervals are large. In the next section we show that a lot of this heterogeneity can be explained by how different types of innovation have disparate effects on revenues and costs.

5.2 The Return of Innovation: demand driven vs cost driven vs both

We follow the same structure as in section 5.1, but instead of pooling all types of innovation, we now categorize the firms into exclusively demand innovators (product and/or marketing innovation), exclusively cost innovators (process and/or organizational innovation) and those that do both types of innovation. The baseline group remains the set of non-innovating firms.

Table 8: Firm performance decomposition I

Dependent variable	Revenues ($p+q$) & Cost of Production ($ac+q$)			Profit Index ($p-ac$)
	Price(p)	Quantity (q)	Average cost (ac)	
Demand	0.067	-0.088	0.057	0.010*
(product ∪ marketing)	(0.093)	(0.123)	(0.093)	(0.006)
Cost	-0.211**	0.617***	-0.223**	0.012**
(process ∪ organizational)	(0.093)	(0.121)	(0.093)	(0.006)
Both	0.208***	-0.183**	0.193***	0.015***
(demand ∩ cost)	(0.067)	(0.090)	(0.068)	(0.005)
R^2	0.614	0.611	0.613	0.063
# observations	7,213	7,213	7,213	7,213

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

When differentiating between demand innovators, cost innovators and those that do both, we find that all innovating firms obtain a similar profit premium, yet they achieve this in very different ways. Firms that focus on process and/or organizational innovation produce products in large quantities. Furthermore, these firms charge on average lower prices for their products and their products have lower average costs than products of non-innovating firms. The opposite is true for firms that do product and/or marketing innovation, who have products for which they charge on average higher prices, produce less and that come with higher average costs than products of non-innovating firms. This is in line with the theory that product and marketing innovation shift out the demand curve, and process and organizational innovation causing a downward shift of the supply curve. Firms that do both types of innovation set higher prices, produce less and have higher costs, suggesting that the demand side mechanism prevails in these firms.

Relating these estimates with the expected impact from demand and cost innovation on productivity from figure 1, we find that cost innovation is indeed significantly associated with lower prices and higher quantities. Also, we find that demand innovation is associated with higher prices, as designated in the left panel of figure 1. Unfortunately, the estimates are imprecise for demand innovators. So it is not clear whether and how exactly demand innovators are different from non-innovating firms. For example, the average negative effect on the quantity produced in product innovators could indicate that demand innovation is not only associated with a shift but also with an inward rotation of the demand curve, which is consistent with the idea that product innovators are higher up on the quality ladder. This is a well-known strategic response of firms in developed economies to low-wage competition from countries like China (Khandelwal, 2010). As our sample consists of Belgian firms, this finding is consistent with that theory.

Table 9 shows the most disaggregated level at which we can identify profit appropriation from different types of innovation.

Table 9: Firm performance decomposition II

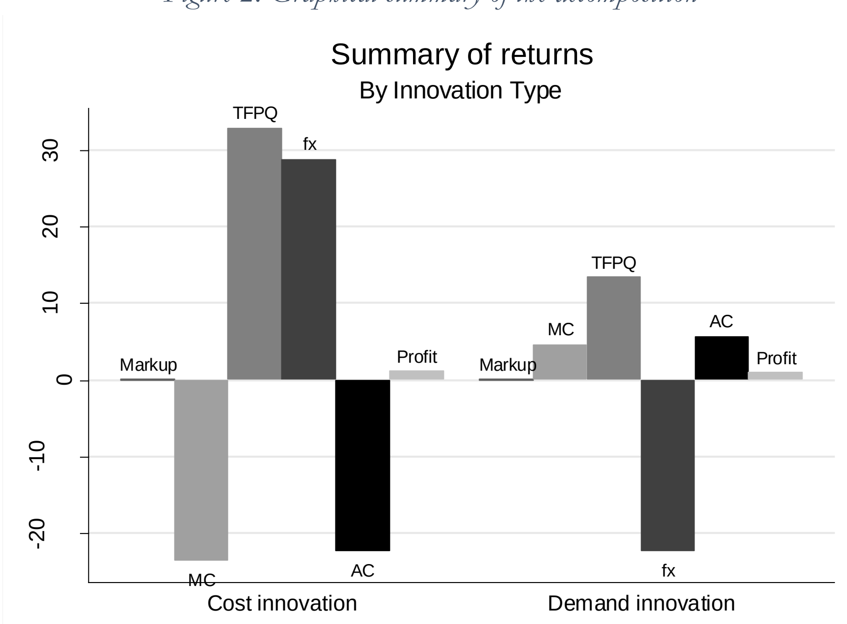
Dependent variable	Revenues $(p+q)$ & Cost of production $(ac+q)$					
	Price $(p=\mu+mc)$		Quantity $(q=tfpq+f(x))$		Average cost (ac)	Profit Index $(p-ac)$
	Markup (μ)	Marginal cost (mc)	Physical Productivity $(tfpq)$	Composite Output $f(x)$		
Demand	0.021**	0.046	0.135	-0.223**	0.057	0.010*
(prod. ∪ mark.)	(0.008)	(0.094)	(0.110)	(0.099)	(0.093)	(0.006)
Cost	0.024**	-0.235**	0.329***	0.288**	-0.223**	0.012**
(proc. ∪ org.)	(0.010)	(0.094)	(0.114)	(0.112)	(0.093)	(0.006)
Both	0.023***	0.185***	-0.027	-0.156**	0.193***	0.015***
(demand ∩ cost)	(0.007)	(0.068)	(0.080)	(0.078)	(0.068)	(0.005)
R^2	0.312	0.617	0.578	0.545	0.613	0.063
# observations	7,213	7,213	7,213	7,213	7,213	7,213

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Regardless of the type of innovation, all innovating firms set a markup that is on average 2-3% higher compared to non-innovating firms. This is a direct indication that firms can appropriate returns of innovation. Yet, the mechanism of how innovation is related to the output price, is very different. Firms that do process and/or organizational innovation have on average about 20% lower marginal costs than non-innovating firms. These firms do not completely pass through their lower costs as they seem to appropriate about 3% by setting higher markups. Although not statistically significant, firms that do product and/or marketing innovation have on average about 5% higher marginal costs than non-innovating firms. On top of that, they also set higher markups than non-innovating firms, resulting in substantially higher output prices. In total, the output price difference between demand innovating and cost innovating firms is about 27%. Note that this does not necessarily imply that product and/or marketing innovation is bad for consumers. It rather indicates that they serve different markets. To the extent that higher prices reflect higher (perceived) quality, utility from consumption will also be higher. For firms that do both cost and demand innovation, it is the latter mechanism that seems to dominate.

Also on the cost-side there are interesting disparities between demand and cost driven innovation. Table 8 showed that cost driven innovating firms produce significantly more quantities than non-innovating firms. This is reflected in the output created by the traditional input factors labor, capital and materials (composite output), but more importantly also shows up in the firm's productivity ($tfpq$). Cost driven innovating firms are about 39% more productive than non-innovating firms. Instead, demand innovators produce products with smaller quantities than non-innovating firms, which shows up in the output produced with their input factors. Yet, more importantly, the technical efficiency premium in demand innovators is far more heterogeneous and not statistically significant. This is an important finding since firm productivity expressed in quantities is the relevant measure for static welfare (Hall, 2011). Figure 2 summarizes the results of the decomposition graphically.

Figure 2: Graphical summary of the decomposition



5.3 Reconciling with earlier literature

Finally, we show how heterogeneity in the innovation-productivity relation in earlier literature can be reconciled with our decomposition. Table 10 decomposes revenue productivity differences across innovation types.

Table 10: TFPR and TFPQ

Dependent variable	Physical Productivity $(tfpq)$	Price (p)	Revenue Productivity $(tfpr)$
Demand	0.135	0.067	0.202***
(prod. ∪ mark.)	(0.110)	(0.093)	(0.072)
Cost	0.329***	-0.211**	0.118
(proc. ∪ org.)	(0.114)	(0.093)	(0.078)
Both	-0.027	0.208***	0.181***
(demand ∩ cost)	(0.080)	(0.067)	(0.0053)
R^2	0.578	0.614	0.36
# observations	7,213	7,213	7,213

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Earlier literature oftentimes documented a positive association between product innovation and tfp, and depending on the country or industry, a positive or negative association between process innovation and tfp. For a review of the literature we refer to Hall (2011) and Mohnen and Hall (2013). In this study, we find a strongly significant revenue premium for firms that do either demand innovation or both demand and cost innovation. In line with many papers in earlier literature, we do not find a significant revenue productivity premium for cost driven innovators. Our findings shed more light on how this finding can be explained. Our analysis suggests this can be explained by opposing effects from cost innovation on a firm's true technical efficiency and the output price they set for their products. While we find strong evidence for a technical efficiency premium in cost innovators, they also charge lower output prices. As revenue productivity is the sum of both, the net effect is not clear ex ante. Depending on the industry or country studied, either effect could prevail, which explains the large heterogeneity in earlier findings documented in figure A-2 of appendix B. Finally, in firms that do both types of innovation, it is the demand mechanism that dominates.

Our findings also contribute to the question whether innovation originates from technology push or demand pull incentives. We refer to Di Stefano, Gambardella and Verona (2012) for an overview on the literature about this research question. For a long time, the literature juxtaposed technology and demand as sources of innovation. Currently, the consensus seems to be that demand and technology are mutually important sources for creating and capturing value from innovation. Although we do not investigate the sources of innovation as such, we see that firms undertake both demand oriented and cost oriented innovation. Moreover, firms seem to be able to capture value from both types of innovation through higher markups. As such, our empirical evidence supports the idea that firms react to both demand pull and technology push incentives in deciding on their innovative activities.

6. Conclusion

In this paper, we contribute to the literature on the relation between innovation, productivity and profitability. To this aim, we construct a novel dataset which combines firm and product level data from the CIS, Prodcom and the National Bank of Belgium. The resulting dataset provides information on firm level innovation practices and production inputs, but also on prices and quantities at the product level for a sample of manufacturing firms in Belgium from 2002-2009. This rich dataset allows us to build on recent advances of the productivity literature to acquire new insights in the profit appropriation mechanism of innovation. In a survey paper of the literature on innovation and productivity, Hall (2011) stressed the importance of this caveat. We are not the first to look into this research question, also Petrin and Warzynski (2011), Cassiman and Vanormelingen (2013), Jaumandreu and Mairesse (2010, 2016) and Jaumandreu and Lin (2018) contributed on this topic. What distinguishes our paper from earlier work, is (i) the availability of product level prices and quantities which allows us to avoid making assumptions on market conduct, (ii) we develop a decomposition model that allows to uncover the underlying mechanism on the link between innovation, productivity and profitability.

The micro level firm performance statistics included in the decomposition model are markups, marginal costs, technical efficiency, output from production factors and average costs. We relate each of these to product and marketing innovation (~demand driven innovation) and process and organizational innovation (~cost driven innovation). Furthermore, we show how these effects add up to price, quantity, revenue, cost and profit differentials across firms.

Comparing innovating to non-innovating firms, we find that demand driven innovation and cost driven innovation come with similar profit premiums through higher markups. However, only firms that do cost driven innovation also have lower marginal costs and a true technical efficiency premium. Furthermore, we find that for firms who do demand innovation, or both demand and cost innovation, output prices are an important determinant of revenue productivity differences. This suggests prices are an important explanation for the large heterogeneity in findings of productivity returns from innovation in earlier studies. Furthermore, the insights in this paper are important for deriving welfare implications from innovation.

All papers come with limitations, and ours is no exception. The decomposition model designated in section 2.1 and section 2.2 is designed at the product level. While our data on the output side is at this level of detail, the data on the input side is not. Therefore, we need to assume a symmetric effect of innovation across years and products within a firm. Although this is also implicitly assumed in earlier work, one ideally wants to go beyond this proposition. Nevertheless, we are convinced this paper does contribute to our understanding on the mechanism of the innovation-productivity relation and we hope that follow-up research can alleviate the remaining concerns stemming from the level of aggregation at which innovation inputs and outputs are available.

References

Abernathy, W. and Utterback, J. (1978). "Patterns of Industrial Innovation" *Technology review*, 80(7): 40-47.

Acemoglu, D., and Linn, J. (2004). "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry" *Quarterly Journal of Economics*, 119(3): 1049–90.

Ackerberg, D.A., Benkard, L., Berry, S. and Pakes, A. (2007). "Econometric Tools for Analyzing Market Outcomes" *Handbook of Econometrics*, Volume 6A, Chapter 63.

Ackerberg, D.A., Caves, K. and Frazer, G. (2015). "Identification Properties of Recent Production Function Estimators" *Econometrica*, 83(6): 2411-2451.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). "Competition and Innovation: An Inverted-U Relationship" *The Quarterly Journal of Economics*, 120(2): 701-728.

Amiti, M. and Konings, J. (2007). "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia" *American Economic Review*, 97(5): 1611-1638.

Amiti, M., Itskhoki, O. and Konings, J. (2014). "Importers, Exporters, and Exchange Rate Disconnect" *American Economic Review*, 104(7): 1942-1978.

Bernard, A.B., Redding, S.J. and Schott, P.K. (2011). "Multi-Product Firms and Trade Liberalization" *The Quarterly Journal of Economics*, 126(3): 1271-1318.

Bilir, L. K. and E. Morales (2019). "Innovation in the Global Firm" *Journal of Political Economy, forthcoming.*

Cassiman, B. and Golovko, E. (2011). "Innovation and Internalization Trough Exports" *Journal of International Business Studies*, 42: 56-75.

Cassiman, B., Golovko, E. and Martínez-Ros, E. (2010). "Innovation, Exports and Productivity" *International Journal of Industrial Organization*, 28: 372-376.

Cassiman, B. and Vanormelingen, S. (2013). "Profiting from Innovation: Firm Level Evidence on Markups" *CEPR Discussion Paper 9703*.

Christensen, L. R., Jorgenson, D.W. and Lau, L. (1973). "Transcendental Logarithmic Production Frontiers" *The Review of Economics and Statistics,* 55(1): 28-45.

Collard-Wexler, A. and De Loecker, J. (2016). "Production Function Estimation with Measurement Error in Inputs" *NBER Working Paper 22437*.

Crépon, B., E. Duguet, and J. Mairesse (1998). "Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level" *Economics of Innovation and new Technology* 7: 115–158.

Crouzet, N, and J Eberly (2018). "Understanding weak capital investment: The role of market concentration and intangibles" *Working paper Jackson Hole Symposium*.

De Loecker, J., Eeckhout, J. and Unger, G. (2018). "The Rise of Market Power and the Macroeconomic Implications" *mimeo.*

De Loecker, J. and Warzynski, F. (2012). "Markups and Firm-Level Export Status" *American Economic Review* 102(6): 2437-2471.

De Loecker, J. (2013). "Detecting Learning by Exporting" *American Economic Journal: Microeconomics*, 5(3): 1–21.

De Loecker, J. and Goldberg, P.K. (2014). "Firm Performance in a Global Market" *The Annual Review of Economics*, 6: 201-227.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K. and Pavcnik, N. (2016). "Prices, Markups and Trade Reform" *Econometrica*, 84(2): 445–510.

Di Stefano, G., Gambardella, A. and Verona, G. (2012). "Technology Push and Demand Pull Perspectives in Innovation Studies: Current Findings and Future Research Directions" *Research Policy*, 41: 1283-1295.

Eckel, C. and Neary, J.P. (2010). "Multi-Product Firms and Flexible Manufacturing in the Global Economy" *The Review of Economic Studies*, 77(1): 188-217.

Forlani, E., Martin, R., Mion, G. and Muûls, M. (2017). "Unraveling Firms: Demand, Productivity and Markups Heterogeneity", *mimeo*.

Geroski, P, Machin, S. and Van Reenen, J. (1993). "The Profitability of Innovating Firms" *RAND Journal of Economics*, 24(2): 198-211.

Griliches, Z. (1998). "R&D and Productivity: The Econometric Evidence" *University of Chicago Press*.

Griliches, Z., and Mairesse, J. (1995). "Production Functions: The Search for Identification" *NBER Working Paper 5067*.

Hall, B. H. (2011). "Innovation and Productivity" *Nordic Economic Policy*, 2: 167–204.

Haltiwanger, J. (2016). "Firm Dynamics and Productivity: TFPQ, TFPR, and Demand-Side Factors" *Economía*, 17(1): 3–26.

Harrison, R., Jaumandreu, J., Mairesse, J. and Peters, B. (2014). "Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data from Four European Countries" *International Journal of Industrial Organization*, 35: 29-43.

Hausman, J. (1996). "Valuation of New Goods Under Perfect and Imperfect Competition" *The Economics of New Goods, Studies in Income and Wealth*, 58: 207-248.

Jaumandreu, J. (2018). "Dangerous Shortcuts: Ignoring Marginal Cost Determinants in Markup Estimation" *mimeo*.

Jaumandreu, J., and Mairesse, J. (2010). "Innovation and Welfare: Results from Joint Estimation of Production and Demand Functions" *NBER Working Paper no. 16221*.

Jaumandreu, J., and Mairesse, J. (2017). "Disentangling the Effects of Process and Product Innovation on Cost and Demand" *Economics of Innovation and New Technology*, 26(1-2): 150-167.

Jaumandreu, J., and Lin, S. (2018). "Prices under Innovation: Evidence from Manufacturing Firms" *CEPR Discussion Paper* 13146.

Khandelwal, A. (2010). "The Long and Short (of) Quality Ladders" *Review of Economic Studies*, 77: 1450-1476.

Kim, K.I., Luo, Y. and Su, Y. (2019). "A Robust Approach to Estimating Production Functions: Replication of the ACF Procedure" *Journal of Applied Econometrics, forthcoming*.

Klette, T., and Griliches, Z. (1996). "The Inconsistency of Common Scale Estimators When Output Prices are Unobserved and Endogenous" *Journal of Applied Econometrics*, 11(4): 343-361.

Levinsohn, J. and Petrin, A. (2003). “Estimating Production Functions Using Inputs to Control for Unobservables” *The Review of Economic Studies*, 70(2): 317-341.

Lieberman, M.B. and Montgomery, D.B. (1988). “First-mover advantages” *Strategic Management Journal*, 9: 41–58.

Mairesse, J. and P. Mohnen (2010). “Using Innovation Surveys for Econometric Analysis” B. H. Hall and N. Rosenberg (eds.), *Handbook of the Economics of Innovation, Volume II*. Amsterdam and New York: Elsevier, pp. 1129-1155.

Mayer, T., Melitz, M.J. and Ottaviano, G.I. (2014) “Market Size, Competition, and the Product Mix of Exporters” *American Economic Review*, 104(2): 495-536.

Mohnen, P., and Hall, B.H. (2013). “Innovation and Productivity: An Update” *Eurasian Business Review*, 3(1): 47-65.

Mothe, C., Nguyen-Thi, U. T. & Nguyen-Van, P. (2015). “Complementarities in organizational innovation practices: evidence from French industrial firms” *Economics of Innovation and New Technology*, 24(6): 569-595.

Olley, B. Y. G. S., and Pakes, A. (1996). “The Dynamics of Productivity in the Telecommunications Equipment Industry” *Econometrica*, 64(6): 1263–1297.

Organization for Economic Co-operation and Development (1992, 1996, 2005). *Oslo Manual*, Paris, 1st, 2nd, 3rd edition.

Peters, B., Roberts, M.J., Vuong, V.A., Fryges, H. (2017). “Estimating Dynamic R&D Choice: An Analysis of Costs and Long-Run Benefits” *RAND Journal of Economics*, 48(2): 409-437.

Petrin, A., and Warzynski, F. (2011). “The Impact of R&D on Quality, Productivity and Welfare” *Mimeo,* University of Minnesota.

Polder, M., Leeuwen, G., Mohnen, P. and Raymond, W. (2010). “Product, Process and Organizational Innovation: Drivers, Complementarity and Productivity Effects” *UNU-MERIT working paper* 2010-35.

Raymond, W., Mairesse, J., Mohnen, P. and Palm, F. (2015). “Dynamic models of R&D, innovation and productivity: Panel data evidence for Dutch and French manufacturing” *European Economic Review*, 78: 285-306.

Solow, R. M. (1957). “Technical Change and the Aggregate Production Function” *The Review of Economics and Statistics*, 39(3): 312-320.

Syverson, C. (2017). “Challenges to Mismeasurement Explanations for the US Productivity Slowdown” *Journal of Economic Perspectives*, 31(2): 165-186.

Teece, D. (1986). “Profiting From Technological Innovation: Implications for Integration, Collaboration, Licencing and Public Policy” *Research Policy*, 15: 285-305.

Van Beveren, I., Bernard, A.B. and Vandenbussche, H. (2012). “Concording EU Trade and Production Data Over Time” M*imeo, Tuck School of Business.*

Van Biesebroeck, J. (2005). “Exporting Raises Productivity in Sub-Saharan African Manufacturing Firm” *Journal of International Economics*, 67(2): 373–391.

Van Leeuwen, G. and Klomp, L. (2006). “On the Contribution of Innovation to Multi-Factor Productivity Growth”, *Economics of Innovation and New Technology*, 15(4-5): 367-390.

Van Reenen, J. (2018). "Increasing Differences Between Firms: Market Power and the Macro-Economy", *CEP Discussion Paper 1576*

Wooldridge, J.M. (2009). "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables" *Economics Letters*, 104(3): 112-114.

Robustness checks

We present robustness checks based on single product firms and perform analysis on subsamples with homogeneous versus heterogeneous quality goods. The regressions include the same set of control variables as in the main body of the paper: : firm age, export status, a self-reported measure of competition, the size of the product portfolio measured by the number of products, the sales share of the product in the firm, a firm size indicator, year dummies and industry dummies.

Single product firms

In single product firms one is sure that the innovation practice is correctly measured. As explained in our data section, we measure our dependent variables at the product-firm-CIS-year level, while our independent variables are measured at the firm-CIS-year level. When looking at single product firms, there are no potential problems regarding identification and interpretation resulting from differences in the level of disaggregation of the variables. The drawback is that the number of observations goes down substantially to 1,275. In order not to control for too much of the variation for identification, we only control for year dummies and industry dummies in these regressions.

Table 11: Single product firms

Dependent variable	Revenues $(p+q)$ & Cost of production $(ac+q)$					
	Price $(p=\mu+mc)$		Quantity $(q=tfpq+f(x))$		Average cost (ac)	Profit Index $(p-ac)$
	Markup (μ)	Marginal cost (mc)	Physical Productivity $(tfpq)$	Composite Output $f(x)$		
Demand	-0.016	0.545**	-0.281	0.381*	0.534**	-0.005
(prod. ∪ mark.)	(0.021)	(0.226)	(0.258)	(0.205)	(0.224)	(0.013)
Cost	0.027	-0.323	0.329	0.520**	-0.290	-0.005
(proc. ∪ org.)	(0.021)	(0.219)	(0.249)	(0.203)	(0.216)	(0.013)
Both	0.013	0.235	-0.289	0.990***	0.254	-0.006
(demand ∩ cost)	(0.015)	(0.173)	(0.211)	(0.157)	(0.171)	(0.010)
R^2	0.340	0.577	0.578	0.285	0.573	0.042
# observations	1,275	1,275	1,275	1,275	1,275	1,275

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Apart from the increased uncertainty on our estimates, which we attribute to the low number of observations, there are some surprising results. First and foremost, the effect we found on higher markups in innovating firms seems to be primarily driven by multi product firms. Second, in single product firms, the difference between demand innovators and non-innovating firms in marginal costs is higher and strongly significant. The sign on physical productivity also flips. Despite not being significant, these results indicate that on average demand innovators have a physical productivity deficit.

Homogeneous quality

The effect of innovation on price could not only reflect an increase in market power, but also increases in quality. While pure market power effects increase producer surplus at the cost of consumer surplus, this is not true for quality effects. Therefore, when assessing price effects of innovation from a welfare point of view, one ideally wants to hold quality constant. It is unlikely that quality is captured by industry fixed effects. Yet, more advanced approaches such as estimating demand functions to obtain measures for quality are not feasible since we have no information on product characteristics and hence have no way to avoid serious endogeneity issues in demand estimation. However, we have information the unit of production. Production quantities in ProdCom are expressed in various measures. We observe that in heterogeneous quality industries like e.g. computers and electronics equipment, most output is reported in 'number of items' while in more homogeneous quality industries like e.g. metals, most output is reported in 'kilograms'. As robustness check, we will do the decomposition on the subsample of products that report kilograms as output measures, under the assumption that such products are homogeneous, or at least more homogeneous, in quality than other products, which alleviates at least some of the concerns on picking up quality effects.

Table 12: Homogeneous quality – Products in kilograms

Dependent variable	Revenues $(p+q)$ & Cost of production $(ac+q)$					
	Price $(p=\mu+mc)$		Quantity $(q=tfpq+f(x))$			
	Markup (μ)	Marginal cost (mc)	Physical Productivity $(tfpq)$	Composite Output $f(x)$	Average cost (ac)	Profit Index $(p-ac)$
Demand	0.020**	0.027	0.094	-0.125	0.039	0.008
(prod. ∪ mark.)	(0.008)	(0.080)	(0.105)	(0.121)	(0.080)	(0.007)
Cost	0.017**	-0.097	0.154	0.493***	-0.104	0.024***
(proc. ∪ org.)	(0.008)	(0.078)	(0.095)	(0.114)	(0.079)	(0.006)
Both	0.009	0.321***	-0.280***	-0.014	0.324***	0.006
(demand ∩ cost)	(0.006)	(0.058)	(0.076)	(0.096)	(0.057)	(0.005)
R^2	0.298	0.274	0.320	0.524	0.268	0.102
# observations	4,762	4,762	4,762	4,762	4,762	4,762

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

Table 12 shows that the findings on higher markups in innovating firms compared to non-innovating firms remains unchanged, which supports our finding that innovation increases market power. Yet, the significance on some of our other findings disappears. Despite the sign of the coefficients and the magnitude of the coefficients remains similar, the finding on lower marginal and average costs and higher physical productivity for cost innovators is now not significant anymore. This is an indication that the significance of the physical productivity effect is especially driven by heterogeneous quality products.

As a second way to account for quality differences across products, we rely on the Rauch (1999) classification.[16] This classification divides goods into three groups: those traded on organized exchanges, those having reference prices and differentiated goods. Possessing a reference price or being listed on an organized exchange indicates that the products are rather homogeneous in quality. Table 13 shows the profit appropriation decomposition for the firms that are active in 4-digit industries that are exclusively or mostly producing homogeneous quality goods.

Table 13: Homogeneous Quality - Rauch

Dependent variable	Revenues $(p+q)$ & Cost of production $(ac+q)$					
	Price $(p=\mu+mc)$		Quantity $(q=tfpq+f(x))$		Average cost (ac)	Profit Index $(p-ac)$
	Markup (μ)	Marginal cost (mc)	Physical Productivity $(tfpq)$	Composite Output $f(x)$		
Demand	0.026*	-0.053	0.036	0.022	-0.013	-0.0153
(prod. ∪ mark.)	(0.015)	(0.171)	(0.194)	(0.232)	(0.171)	(0.0146)
Cost	0.030**	-0.139	-0.093	1.176***	-0.110	0.00153
(proc. ∪ org.)	(0.013)	(0.164)	(0.203)	(0.195)	(0.164)	(0.0132)
Both	0.013	0.555***	-0.680***	0.121	0.585***	-0.0178
(demand ∩ cost)	(0.012)	(0.130)	(0.141)	(0.160)	(0.129)	(0.0125)
R^2	0.472	0.321	0.278	0.528	0.313	0.156
# observations	1,606	1,606	1,606	1,606	1,606	1,606

Table 14: Heterogeneous Quality - Rauch

Dependent variable	Revenues $(p+q)$ & Cost of production $(ac+q)$					
	Price $(p=\mu+mc)$		Quantity $(q=tfpq+f(x))$		Average cost (ac)	Profit Index $(p-ac)$
	Markup (μ)	Marginal cost (mc)	Physical Productivity $(tfpq)$	Composite Output $f(x)$		
Demand	0.001	0.111	0.227	-0.266*	0.104	0.008
(prod. ∪ mark.)	(0.014)	(0.137)	(0.156)	(0.152)	(0.136)	(0.008)
Cost	0.003	-0.274*	0.438**	0.120	-0.281*	0.011
(proc. ∪ org.)	(0.016)	(0.148)	(0.175)	(0.158)	(0.147)	(0.008)
Both	0.008	0.056	0.140	-0.132	0.055	0.009
(demand ∩ cost)	(0.011)	(0.101)	(0.124)	(0.123)	(0.101)	(0.007)
R^2	0.318	0.579	0.553	0.544	0.571	0.060
# observations	3,391	3,391	3,391	3,391	3,391	3,391

Notes: All dependent variables are in logs and standard errors are bootstrapped. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level.

The results are remarkably similar to those of table 13. The markup effect in our study seems to be driven by homogeneous products, while the physical productivity effect seems to be driven by heterogeneous products.

[16] The Rauch-classification can be downloaded from https://econweb.ucsd.edu/~jrauch/rauch_classification.html. The classification is in the SITC format. Using concordance tables between SITC, HS2007, CN2007 and Prodcom2007, we were able to obtain Rauch codes for about 30% of the products. We then took the most occurring Rauch code of products in the 4-digit industry to classify 4-digit industries as homogeneous or heterogeneous goods producers.

Appendix A – Estimation of the production function

A.1 The quantity production function

We obtain estimates for β_l, β_k and β_m from a quantity production function. We depart from the standard Cobb-Douglas case and rely on a Translog Production function (Christensen et al., 1973). This functional form offers the advantage that it allows to obtain output elasticities that vary across firms and time because of heterogeneity in input intensities. This will be particularly useful when estimating markups (see infra). The log-linearized Translog production function is:

$$y_{ijt} = \boldsymbol{\beta} \boldsymbol{x}'_{\boldsymbol{ijt}} + \omega_{jt} + \varepsilon_{ijt} \tag{1}$$

In which the subscripts i, j, t refer to product, firm and year. $\boldsymbol{\beta}$ denotes the vector of coefficients that belong to the set of production inputs $\boldsymbol{x}'_{\boldsymbol{ijt}} = \{l_{ijt}, k_{ijt}, m_{ijt}, l^2_{ijt}, k^2_{ijt}, m^2_{ijt}, l_{ijt}k_{ijt}, l_{ijt}m_{ijt}, k_{ijt}m_{ijt}, l_{ijt}k_{ijt}m_{ijt}\}$ in which l, k and m refer to employment (measured in hours worked), capital (tangible fixed assets) and materials (intermediate inputs). The residual error term consists of two components, ω_{jt} and ε_{ijt}. The part of planned production that cannot be explained by the factor inputs is denoted as ω_{jt}. The true exogenous error term (e.g. strikes, machine breakdowns) is denoted as ε_{ijt}. In a revenue production function, y refers to turnover and the residual of equation (1) to TFPR, while in a quantity production function, y refers to quantities and the residual of equation (1) to TFPQ.

In a traditional setting, the production function is firm (j) specific. Since our dataset reports for each firm (j) the quantity sold and the associated revenues of all products (i) that the firm sells, we can go one step further. To do so, we make the assumption that multi-product firms have the same productivity ω_{jt} in all its products. This is how productivity is traditionally modeled in multi-product firms (e.g. Bernard, Redding, and Schott, 2011; De Loecker et al., 2016). This assumption is of course redundant for single product firms, and implicitly assumed in other papers where product level data is not available. Our notion of the production function assumes a product specific production technology instead of a firm specific one. This approach is commonly used in work with similar data (De Loecker et al., 2016 and Forlani et al., 2017). While this approach allows to maximally exploit the variation in prices and quantities on the output side, it does require imposing assumptions on the input side. Data on production inputs is only available at the firm level, which means that inputs need to be allocated across products within a firm. We follow Syverson et al. (2008) and do this based on the sales share of the product within the firm.[17] Furthermore, our innovation measures are at the firm level, hence we need to

[17] A theoretically superior solution would be to follow De Loecker et al. (2016) and use single product firms to estimate quantity production functions, for which allocating inputs across products is irrelevant, and assign these technology parameters to products in multiproduct firms. However, our sample size is not sufficient to follow this approach. Therefore, we proceed by pooling single and multiproduct firms and allocate inputs to products in a firm based on sales shares as in Syverson et al. (2008). Only in case of perfectly competitive markets or constant markups across products, the sales share will effectively align with the share in input expenditures. This implies that inputs, except in the single product firms in our sample for which this issue is irrelevant, may be imperfectly allocated across products in a firm. To control for potential biases in the production function coefficients stemming from this allocation, we include the number of products produced and the sales share of the product within the firm as additional variables in our model. Eckel and Neary (2010); Mayer, Melitz and Ottaviano (2014) and De Loecker et al. (2016) found strong evidence that the sales share is positively related with markups and negatively related with marginal costs. This suggests that any potential bias introduced by imperfect allocation of the input expenditures is correlated with the market share of the product in the firm. Therefore, we expect that including the market share of the product within the firm both in the production function estimation and in the second stage of our procedure where we relate product level firm performance measures to innovation will theoretically solve a potential bias stemming from allocating inputs in multiproduct firms as in Syverson et al. (2008).

assume there is a symmetric effect of innovation across products within a firm. While this assumption is plausible for organizational and to a large extent also process innovation, this assumption could be more problematic for product and marketing innovation, which are likely product specific. However, to the best of our knowledge, there exists no dataset that collects innovation practices at the product level, so earlier studies implicitly made the same assumptions as we do. The paper also contains a robustness check based on single product firms, for which these possible issues are of course irrelevant.

When the dependent variable is expressed in quantities and the independent variables in monetary values, this could result in biased coefficient estimates due to unobserved firm-product input price variation from the industry wide input price deflator, see De Loecker et al. (2014) for a theoretical overview. We follow De Loecker et al. (2016) and proxy for unobserved input prices using a polynomial of the firm's output price and market share and also include product dummies. The rational of this approach is that manufacturing high quality products, and thus expensive products, requires high quality, and thus expensive, inputs. For internal consistency, we also allow the input prices to depend on the innovation status. Denoting the product-firm input price deviation from the industry wide deflator with w_{ijt}, prices with p_{ijt}, market share with ms_{ijt} and innovation with inn_{jt}, the adjusted quantity production function is:

$$q_{ijt} = \boldsymbol{\beta x'_{ijt}} + w_{ijt}\left(p_{ijt}, ms_{ijt}, inn_{jt}\right) + \omega_{jt} + \varepsilon_{ijt} \qquad (2)$$

Estimating equation (6) using OLS will result in biased coefficients because of the well-known simultaneity problem when estimating production functions, i.e. the firm has a certain level of productivity (ω_{jt}) in function of which it chooses how much labor and materials to use as production inputs.[18] To avoid biases in the β_l and β_m coefficients, we apply the control function approach which was introduced by Olley and Pakes (1996).[19] The idea is that firms signal their productivity (ω_{jt}), which the econometrician is agnostic about, through their investment demand. Under the condition of strict monotonicity, productivity can then be obtained by inverting the investment demand function. This investment demand function relies on a scalar unobservable assumption, i.e. that productivity is the only unobservable in the investment equation. We follow Van Biesebroeck (2005) and Amiti and Konings (2007) and relax this assumption by including the innovation status of the firm and prices in the investment demand function. Based on this model, substituting ω_{jt} from equation (2) by the following equation then allows unbiased identification of β_l and β_m:

$$inv_{jt} = f(\omega_{jt}, k_{jt}, inn._{jt}, p_{ijt}) \rightarrow \omega_{jt} = f^{-1}\left(inv_{jt}, k_{jt}, inn._{jt}, p_{ijt}\right) \qquad (3)$$

In practice, equation (3) is approximated with a higher order polynomial in investment demand and capital and interactions thereof with a firm's innovation status and the output price. Since capital is both a part of this control function and the set of coefficients that need to be identified in order to obtain ω, Olley and Pakes

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18 Production, and hence also the choice of production inputs, is increasing in ω. Not taking into account unobserved productivity differences results in upward biased β_l and β_m coefficients when estimating equation (2) using OLS. Capital is commonly assumed to be a state variable, i.e. investments that a firm makes, which results in changes in the capital stock, take one year to become productive (see Ackerberg, Benkard, Berry and Pakes, 2005 for a discussion). As a result, there is no correlation between ω and k, and hence no simultaneity bias on β_k.

19 Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015) suggest using material inputs instead because of lumpy reporting of investments, i.e. assuming that firms signal their productivity through their materials purchases. However, since we estimate quantity production functions using the one-step Wooldridge (2009) approach, contemporaneous and lagged material expenditures are used as independent variable and instrument, which precludes us from using it as proxy variable as this would result in a violation of the exclusion restriction of lagged materials as instrument.

(1996) use a second stage for identifying the capital coefficient in which they assume productivity to follow a first order Markov process, i.e. current productivity is a function of last-year's productivity and an unexpected shock. Since a firm's expectations of productivity can depend on its innovation activity, we include the innovation status in the law of motion of productivity as in Cassiman and Vanormelingen (2013) and Doraszelski and Jaumandreu (2013). This results in the following law of motion for productivity growth:

$$\omega_{jt} = g\left(\omega_{jt-1}\right) + inn._{jt} + \xi_{jt} \tag{4}$$

In which $g(.)$ is an autoregressive function of order one and ξ_{jt} represents the news that the firm receives on its change in productivity compared to the year before. Depending on when the firm receives this news, the choice of materials and labor can still be correlated with ξ_{jt} (Ackerberg, Caves and Frazer, 2015). We follow Wooldridge (2009) and directly substitute equations (3) and (4) in equation (2) and instrument the labor and materials variables with their lags to avoid the coefficients to suffer from any potential simultaneity bias. For the capital coefficient, we follow Collard-Wexler and De Loecker (2016) and use the actual recorded investment in $t-1$ as instrument for capital to avoid biases from measurement error. We also follow Kim, Luo and Su (2019) who showed that using additional lags as instruments for the capital variable improves the robustness of the estimates. The specification that we estimate with a one-step GMM estimator is the following:

$$q_{ijt} = \boldsymbol{\beta x'_{ijt}} + f^{-1}\left(inv_{jt-1}, k_{jt-1}, inn._{jt-1}, p_{ijt-1}\right) + inn._{jt} + w_{ijt}\left(p_{ijt}, ms_{ijt}, inn_{jt}\right) + \boldsymbol{z_{ijt}} + \xi_{it} + \varepsilon_{ijt} \tag{5}$$

The vector $\boldsymbol{z_{ijt}}$ contains a set of control variables: product dummies, year dummies, product unit dummies, the number of products in the firm's product portfolio and the sales share of the product within the firm. With the estimates of equation (9) at hand, we obtain the production function elasticities and $\widehat{tfpq}_{ijt}$ from:

$$\begin{aligned}
\hat{\theta}^L_{ijt} &= \hat{\beta}_l l_{ijt} + 2\hat{\beta}_{ll} l_{ijt} + \hat{\beta}_{lk} k_{ijt} + \hat{\beta}_{lm} m_{ijt} + \hat{\beta}_{lkm} km_{ijt} \\
\hat{\theta}^K_{ijt} &= \hat{\beta}_k k_{ijt} + 2\hat{\beta}_{kk} k_{ijt} + \hat{\beta}_{lk} l_{ijt} + \hat{\beta}_{km} m_{ijt} + \hat{\beta}_{lkm} lm_{ijt} \\
\hat{\theta}^M_{ijt} &= \hat{\beta}_m m_{ijt} + 2\hat{\beta}_{mm} m_{ijt} + \hat{\beta}_{lm} l_{ijt} + \hat{\beta}_{km} k_{ijt} + \hat{\beta}_{lkm} lk_{ijt} \\
\widehat{tfpq}_{ijt} &= q_{ijt} - \hat{\beta}_l l_{ijt} - \hat{\beta}_{ll} l^2_{ijt} - \hat{\beta}_k k_{ijt} - \hat{\beta}_{kk} k^2_{ijt} - \hat{\beta}_m m_{ijt} - \hat{\beta}_{mm} m^2_{ijt} \\
&\quad - \hat{\beta}_{lk} lk_{ijt} - \hat{\beta}_{lm} lm_{ijt} - \hat{\beta}_{km} km_{ijt} - \hat{\beta}_{lkm} lkm_{ijt}
\end{aligned} \tag{6}$$

By estimating $\boldsymbol{tfpq}$, one also immediately has the estimate of what we label in the decomposition as composite output, denoted with $\boldsymbol{f(x_{ijt})}$, at hand. This is output that the firm produces with its inputs, denoted with $\boldsymbol{\beta x'_{ijt}}$ in equation (1).

Ideally, one could run the production function estimation procedure outlined above for each product separately. However, the number of parameters to be estimated is substantial, so sample sizes are typically too small to do so. Hence, it is standard practice in the literature to estimate the production function at the two-digit level. We remind the reader that there is heterogeneity across time and firms in the estimated production function elasticities from two sources: first because we allow varying technology parameters between industries and secondly because the Translog production function accounts for differences in input intensity. Table A-1 shows for each sector the median output elasticities calculated as in equation (6). We show the output elasticities from a simple regression (OLS) as in equation (1) without accounting for potential endogeneity biases or endogenous productivity processes, except that we include output prices to control for input price biases. Next to this, we show the results of the extended model that was outlined above to structurally account for any biases in the coefficients according to state of the art techniques of the productivity literature.

Table A- 1: Production Function Elasticities I

Industry	$\hat{\theta}_l$		$\hat{\theta}_k$		$\hat{\theta}_m$		RTS	
	OLS	WR1	OLS	WR1	OLS	WR1	OLS	WR1
10 - 12: Food, Beverages & Tobacco	0.17	0.17	0.01	0.01	0.82	0.83	1.00	1.01
13 - 15: Textiles, Apparel & Leather	0.23	0.15	0.02	0.06	0.74	0.78	1.00	1.00
16 - 18: Wood, Paper & Printing	0.21	0.25	0.03	0.00	0.76	0.73	1.00	1.00
20 - 21: Chemicals & Pharma	0.11	0.09	0.02	0.02	0.88	0.90	1.01	1.00
22 - 23: Rubber & Non-Metallic Minerals	0.20	0.17	0.03	0.04	0.78	0.79	1.01	1.00
24 - 25: Metals	0.23	0.23	0.03	0.00	0.74	0.77	1.00	1.01
26 - 28: Computers, Electrical & Machinery	0.29	0.32	0.02	0.00	0.70	0.68	1.01	1.00
29 - 30: Vehicles & Transport Equipment	0.24	0.14	0.04	0.11	0.72	0.84	1.00	1.06
31 - 33: Furniture, Other Manuf. & Repair	0.23	0.19	0.02	0.03	0.75	0.79	1.00	1.01
Average	0.17	0.16	0.02	0.02	0.81	0.82	1.00	1.00

Notes: We removed some observations for which the ratio of the capital cost, wage bill, material inputs or the sum of those exceeded the turnover of the product to an implausible extent.

Both for the simple (OLS) and the extended model (WR1), the returns to scale are very close to 1. While the OLS and WR1 model show similar labor and materials coefficients, the capital coefficient is rather low, especially with the WR1 estimator.[20] While not apparent from table A-1, there are also observations for which the production function elasticities are negative. This indicates that the production function is not well behaved. A production function is expected to have positive marginal products for all inputs and to be quasi-concave (Cassiman and Vanormelingen, 2013). The marginal product of an input is positive when its output elasticity is positive. For observations that violate this condition, we give up on sector heterogeneity in the output elasticities and assign elasticities based on a manufacturing-wide estimation of the extended production function. If based on these parameters the elasticity still remains negative, we drop the observation from our sample. Table A-2 shows the output elasticities across sectors after this procedure. The capital coefficient is now more in line with theoretically expected values.[21] Moreover, table A-2 shows for each sector the number of single- and multi-product observations used for estimating the production function. As is apparent from the table, the largest part of our sample in terms of observations consists of multi-product firms.

Table A- 2: Production Function Elasticities II

Industry	$\hat{\theta}_l$	$\hat{\theta}_k$	$\hat{\theta}_m$	RTS	Estimation sample (#obs)			Estimation sample (#firms)		
					Total	Single	Multi	Total	Single	Multi
10 - 12: Food, Beverages & Tobacco	0.18	0.02	0.80	1.01	2140	135	2005	232	60	175
13 - 15: Textiles, Apparel & Leather	0.17	0.06	0.74	1.00	860	99	761	121	42	87
16 - 18: Wood, Paper & Printing	0.26	0.02	0.69	0.99	458	89	369	85	33	52
20 - 21: Chemicals & Pharma	0.13	0.03	0.85	1.01	2657	106	2551	130	38	96
22 - 23: Rubber & Non-Metallic Minerals	0.18	0.04	0.79	1.00	1211	300	911	220	107	119
24 - 25: Metals	0.25	0.02	0.76	1.00	1013	271	742	223	122	120
26 - 28: Computers, Electrical & Machinery	0.32	0.01	0.58	1.00	1014	285	729	208	103	116
29 - 30: Vehicles & Transport Equipment	0.20	0.07	0.84	1.10	273	105	168	59	28	35
31 - 33: Furniture, Other Manuf. & Repair	0.17	0.06	0.85	1.02	521	93	428	85	33	57
Average (Total)	0.19	0.03	0.78	1.00	(10147)	(1483)	(8664)	(1363)	(566)	(857)

[20] In this model, lagged capital and lagged investment demand are included in the control function for unobserved productivity. However, capital is correlated over time, so including the control function lowers the estimate of the current capital stock.

[21] The capital coefficients ultimately used to obtain physical productivity are thus oftentimes obtained from manufacturing-wide technology parameters. There are few negative materials output elasticities, so here we do have variation in elasticities from technology differences, which is important as this coefficient will be used for obtaining markup estimates.

A.2 Average costs

The average cost represents the per unit cost related to the production inputs, being labor, capital and materials. The wage bill and intermediate input expenditures are readily available in the data. To proxy for the cost of capital, we take reported depreciation and add the opportunity cost of capital, measured as the real interest rate, and multiply this with the capital stock. We use a gross fixed capital deflator to obtain the real capital cost. The wage bill is deflated with a GDP deflator and intermediate inputs are deflated using a producer price index, both obtained from Eurostat.

A.3 Markups and Marginal costs

As in Cassiman and Vanormelingen (2013), we rely on the markup estimation approach of De Loecker and Warzynski (2012), which allows to obtain markup estimates without assumptions on market conduct or any functional form on market demand. Instead, the methodology assumes cost minimization with regard to a variable input that is free of adjustment costs. Starting from the Lagrangian cost function that is associated with the production function in equation (1):

$$\mathcal{L}\left(X_{ijt}^{1}, \dots, X_{ijt}^{V}, K_{ijt}, mc_{ijt}\right) = \sum_{v=1}^{V} P_{ijt}^{x^{v}} X_{ijt}^{v} + r_{ijt}K_{ijt} + mc_{ijt}(Q_{ijt} - Q_{ijt}(.)) \tag{7}$$

In which $X_{ijt}^{1}, \dots, X_{ijt}^{V}$ refer to the variable inputs used in production, K_{ij} and r_{ijt} to capital and its cost, mc_{ijt} to marginal cost at the given level of production, $P_{ijt}^{x^{v}}$ to the price of the variable inputs and Q_{ijt} the currently produced quantity. Take the first order condition to a variable input used in the production of product j:

$$\frac{\delta \mathcal{L}_{ijt}}{\delta X_{ijt}^{V}} = P_{ijt}^{x^{V}} - mc_{ijt}\frac{\delta Q_{ijt}(.)}{\delta X_{ijt}^{V}} = 0 \tag{8}$$

Now rearrange both terms in this derivative and multiply both with the ratio of the physical input quantity from the variable production factor to physical product output quantity of the product $\frac{X_{ijt}^{V}}{Q_{ijt}}$:

$$P_{ijt}^{x^{V}} \frac{X_{ijt}^{V}}{Q_{ijt}} \frac{1}{mc_{ijt}} = \frac{\delta Q_{ijt}(.)}{\delta X_{ijt}^{V}} \frac{X_{ijt}^{V}}{Q_{ijt}} \tag{9}$$

The right hand side of equation (9) is equal to the output elasticity of the variable input, which we can estimate as shown in section A.1 without assumptions on market conduct. Now define the markup $(\sim\mu_{ijt})$ as the ratio of the output price of product j to the marginal cost of product j: $\mu_{ijt} = \frac{P_{ijt}^{Q}}{mc_{ijt}}$. Then $mc_{ijt} = \frac{P_{ijt}^{Q}}{\mu_{ijt}}$. Now substitute this expression of the marginal cost in equation (9):

$$\mu_{ijt} \frac{P_{ijt}^{x^{V}}}{P_{ijt}^{Q}} \frac{X_{ijt}^{V}}{Q_{ijt}} = \frac{\delta Q_{ijt}(.)}{\delta X_{ijt}^{V}} \frac{X_{ijt}^{V}}{Q_{ijt}} \tag{10}$$

Denoting the output elasticity of the variable input with β_{ijt}^{v} and the expenditure share of this variable input in the revenue of the product with α_{ijt}. Note that we observe this in the data. We can then obtain an estimate for the markup of product j from:

$$\hat{\mu}_{ijt} * \alpha_{ijt} = \hat{\beta}_{ijt}^{V} \rightarrow \hat{\mu}_{ijt} = \frac{\hat{\beta}_{ijt}^{V}}{\alpha_{ijt}} \tag{11}$$

The inputs in our production framework are labor, capital and materials. While capital is a fixed factor of production, labor and especially materials are more flexible production factors, see Ackerberg, Caves and Frazer (2015) for a discussion. As is common in empirical work that uses this methodology to obtain markup estimates, we use the materials elasticity from equation (9) to obtain an estimate for the markup of product j:[22]

$$\hat{\mu}_{ijt} = \frac{\hat{\theta}_{ijt}^{M}}{\alpha_{ijt}} \quad (12)$$

With the estimated markup at hand and product level prices in our dataset, it is straightforward to obtain an estimate for the marginal cost of the product from:

$$\widehat{mc}_{ijt} = \frac{P_{ijt}^{Q}}{\hat{\mu}_{ijt}} \quad (13)$$

We now have all firm performance measures that we need to estimate equation (4) in the main body of the paper.

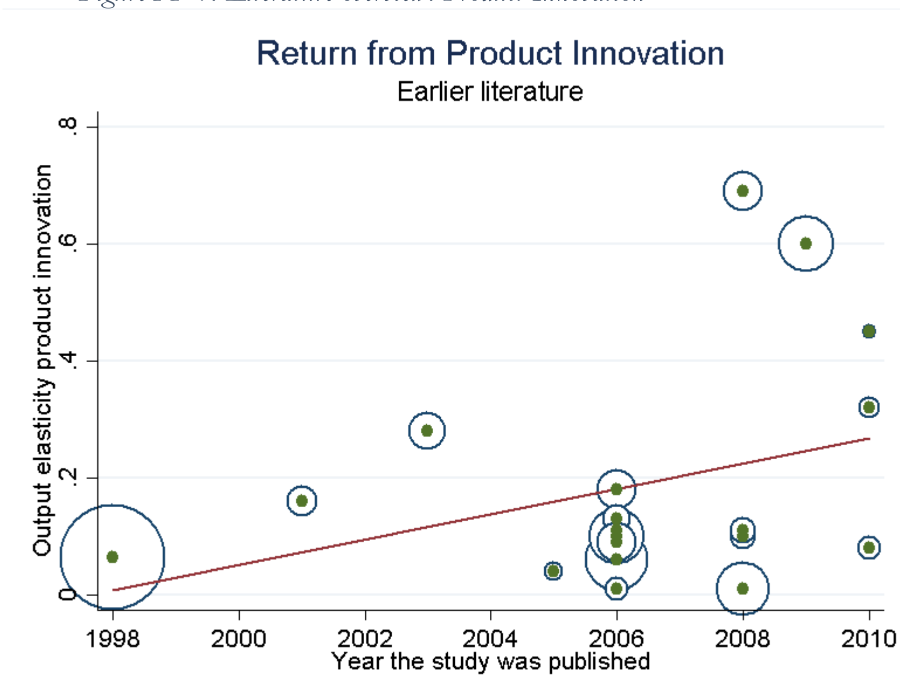
[22] As noted by Jaumandreu (2018), the markup estimates could be biased because of unobserved adjustment costs in some of the production factors, which makes the problem of cost minimization dynamic. Ignoring this could cause biased estimates of the output elasticities and thus biased markups. This potential bias can be mitigated by using the sum of the labor and materials elasticities and the sum of material expenditures and the wage bill to total revenues as cost share. An implicit assumption is then that labor is a variable production factor. Since we estimate product specific production functions, this implies we assume that labor can be flexibly allocated across products within a firm. Our results are qualitatively robust to taking this approach.

Appendix B: Additional tables and figures

B.1 Literature overview

The figures below illustrate the heterogeneity in the innovation economics literature so far on the output elasticity of product innovation and process innovation. We do not include figures on organizational and marketing innovation as the literature did not focus on these types of innovation. Although there is substantial heterogeneity across studies in measured returns from product innovation, all studies do agree on positive returns for productivity.

Figure A- 1: Literature overview: Product Innovation

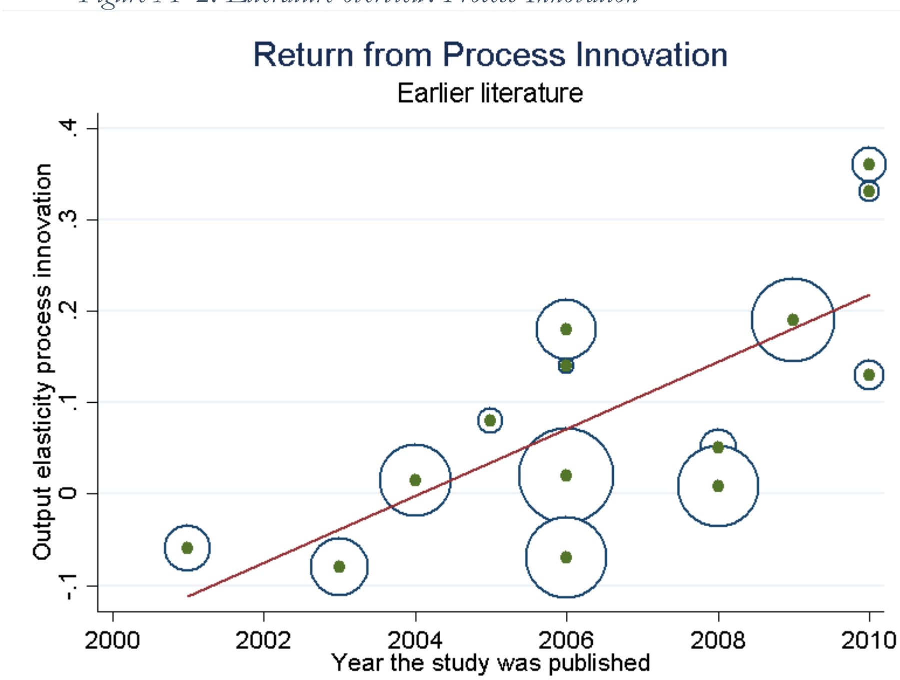


Notes: The size of the circle indicates the number of citations received by the paper.[23]

[23] The studies comprised in this table are Crépon, Duguet and Mairesse (1998), Griffith, Huergo, Harrisson and Mairesse (2006), Hall, Lotti and Mairesse (2008, 2009), Loof and Heshmati (2006), Roper, Du and Love (2008), Chudnovsky, Lopez and Pupato (2006), Benavente (2006), Janz, Loof and Peters (2003), Loof, Heshmati, Asplund and Naas (2001), Van Leeuwen and Klomp (2006), Masso and Vahter (2008), Raffo, Lhuilery and Miotti (2008), Duguet (2006), Mairesse and Robin (2010), Musolesi and Huiban (2010), Mairess, Mohnen and Kremp (2005), Siedschlag, Zhang and Cahill (2010), Parisi, Schiantarelli, and Sembenelli (2006).

Also the literature on process innovation does not show ubiquitous findings on the returns from process innovation for productivity. While there is a consensus on positive productivity returns for product innovation, this is not necessarily true for process innovation. Especially earlier studies did find negative returns from process innovation, while recent studies seem to agree on positive returns from process innovation for productivity. This is intriguing, as process innovation typically aims at reducing production costs and optimizing the production process, which should show up in productivity. However, this could be explained by imprecise measurement of productivity. As noted by Hall (2011): "*the mixed evidence on returns from process innovation is primarily due to the fact that we are not able to measure the real quantity effect of process innovation, which is the relevant quantity for social welfare. We can only measure the real revenue effect, which combines the impact of innovation on both quantity and price.*". The productivity measures used in the studies represented in the figure below are based on productivity measures that do not only reflect technical efficiency, but are likely confounded by market power.

Figure A- 2: Literature overview: Process Innovation



Notes: The size of the circle indicates the number of citations received by the paper.[24]

[24] The studies comprised in this table are The studies comprised in this table are Griffith, Huergo, Harrisson and Mairesse (2006), Hall, Lotti and Mairesse (2008, 2009), Loof and Heshmati (2006), Roper, Du and Love (2008), Huergo and Jaumandreu (2004), Chudnovsky, Lopez and Pupato (2006), Janz, Loof and Peters (2003), Loof, Heshmati, Asplund and Naas (2001), Masso and Vahter (2008), Mairesse and Robin (2010), Musolesi and Huiban (2010), Mairess, Mohnen and Kremp (2005), Siedschlag, Zhang and Cahill (2010), Parisi, Schiantarelli, and Sembenelli (2006).

B.2 Principal Component Analysis

Table 1 in the paper shows that frequency of different innovation combinations. To investigate how we can meaningfully reduce the dimensionality of this matrix, we use we use principal component analysis, which is a data reduction method that is typically used to summarize multivariate data in fewer dimensions. Table A-1 shows the results of applying principal component on the aggregated innovation measures, table A-2 shows the results when including all questions from the innovation survey separately.

Table A- 3: PCA aggregate innovation categories

	Principal Component Analysis	
	Component 1	Component 2
Product Innovation	0.45	-0.68
Process Innovation	0.52	0.21
Organizational Innovation	0.16	0.67
Marketing Innovation	0.56	-0.20
Eigenvalue	1.26	1.03

Notes: We follow Kaiser's rule and only retain those components with an eigenvalue larger than 1.

Table A- 4: PCA all CIS questions

	Principal Component Analysis		
New or significantly improved …	Component 1	Component 2	Component 3
Product innovation			
… Goods	0.12	0.48	0.23
… Services	0.27	0.16	-0.02
Process Innovation			
… Innovation in methods of manufacturing	0.28	0.34	-0.37
… Logistics, delivery or distribution methods for your inputs	0.37	0.21	-0.31
… Supporting activities for your processes	0.39	0.17	-0.34
Organizational Innovation			
… Business practices for organizing procedures	0.41	-037	0.00
… Methods of organizing responsibilities & decision making	0.39	-0.44	0.07
… Methods of organizing external relations	0.35	-0.33	0.18
Marketing Innovation			
… Aesthetic design or packaging	0.22	0.27	0.53
… sales or distribution methods	0.23	0.17	0.53
Eigenvalue	2.25	1.36	1.20

Notes: We follow Kaiser's rule and only retain those components with an eigenvalue larger than 1. An overview of the precise questions on the innovation activities can be found in appendix C.

Figure A- 3: PCA on the four aggregate innovation types

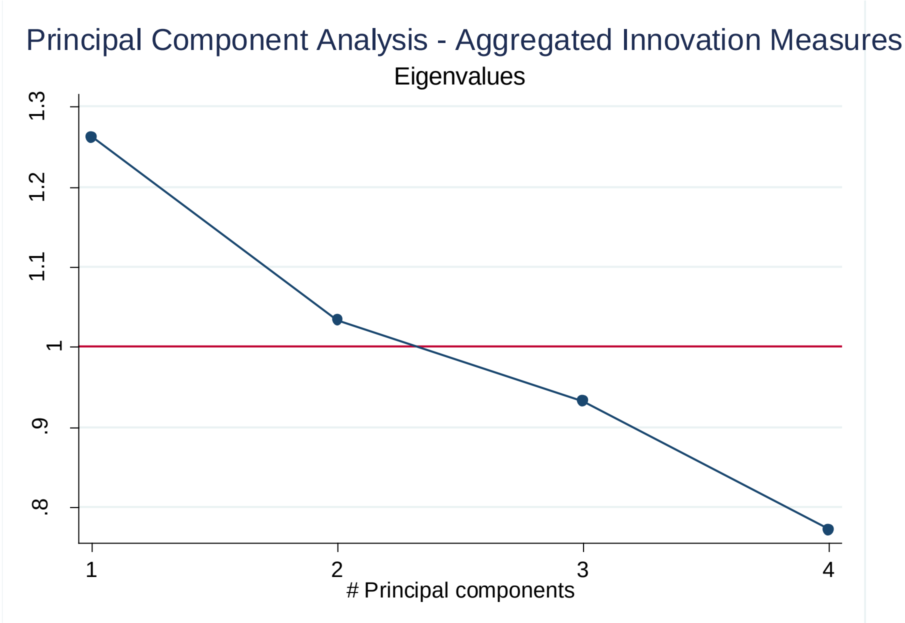
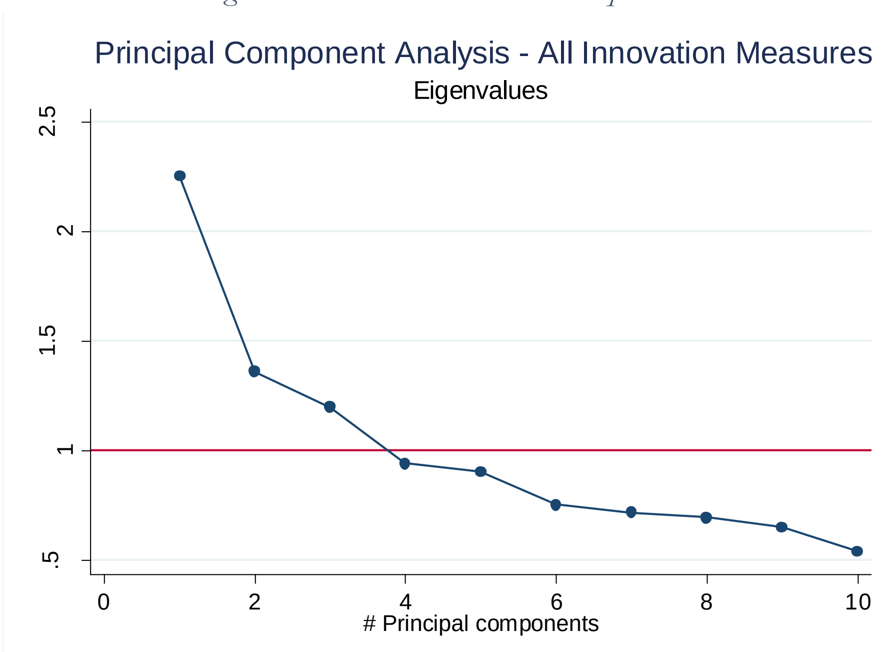


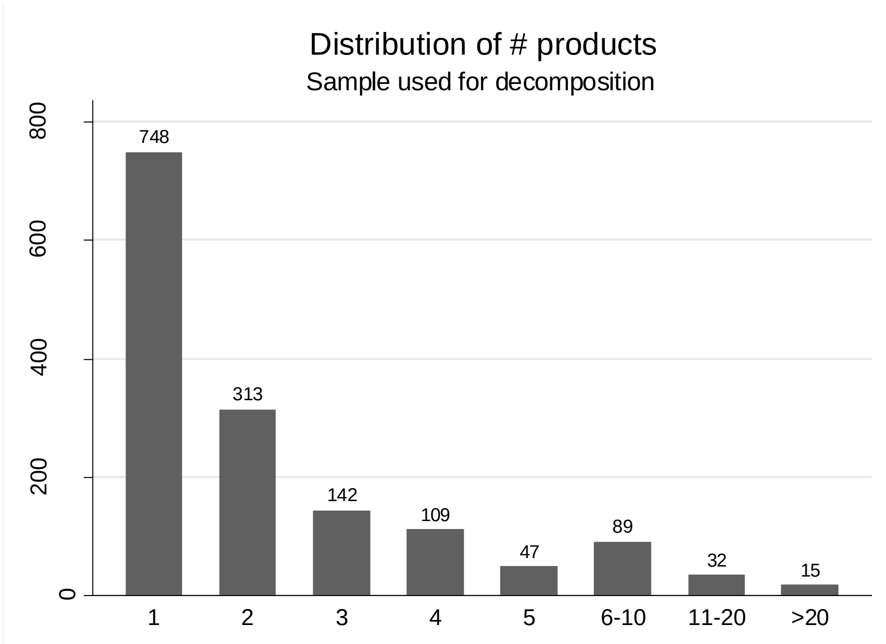
Figure A- 4: PCA on all innovation questions



B.3 Additional summary statistics

B.3.1 Summary statistics on the product portfolio and innovation

Figure A- 5: The number of firms in our sample by product portfolio size



Notes: The x-axis shows the number of products.

Table A- 5: Innovation intensity by product portfolio size

	1 Product	2 Products	3 Products	4 Products	5 Products	6-10 Products	11-20 Products	> 20 products
Demand (prod. ∪ mark.)	14%	12%	15%	14%	16%	12%	8%	7%
Cost (proc. ∪ org.)	14%	12%	15%	12%	16%	12%	5%	10%
Both (demand ∩ cost)	40%	40%	42%	50%	47%	52%	73%	66%

Notes: Summary statistics are for the sample that is used in the decomposition.

Table shows the ratio of firms that innovate in function of the number of products they make. The larger the product folio, the more likely it is that a firm does both demand and cost driven innovation. Doing exclusively demand or cost innovation happens less after the product portfolio size threshold of 5 products is exceeded.

B.3.2 Summary statistics on innovation

Table A- 6: Summary statistics by type of innovation (in 2005 euro)

Median	No innovation	Demand driven (Prod. ∪ Mark.)	Cost driven (Proc. ∪ Org.)	Both demand and cost
Turnover (thousands)	5,746	18,063	15,480	55,953
Added Value (thousands)	1,662	5,365	4,733	15,887
Employment	35	76	66	201
Labor Productivity	54,158	68,238	63,780	81,198
Material expenditures (thousands)	4,164	12,679	11,317	40,744
Tangible Fixed Assets (thousands)	778	1,925	2,279	7,462
Number of products	3	4	3	6

Notes: Summary statistics are for the sample that is used in the decomposition.

From these tables we learn that firms that do no innovation are clearly smaller, basically on all variables that are shown. Firms that do exclusively demand or cost driven innovation have similar statistics, while firms that do both demand and cost innovation are clearly even larger. Given that the firms doing no innovation is our baseline group, this suggests adding the appropriate set of control variables is important in our analysis.

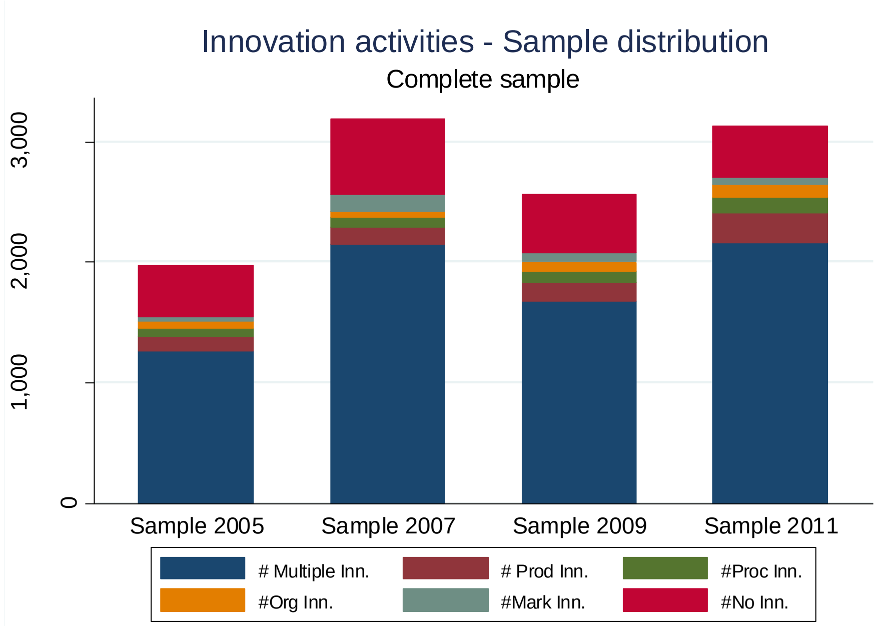
Table A- 7: Types of innovation across industries

Industry	No innovation	Demand driven (Prod. ∪ Mark.)	Cost driven (Proc. ∪ Org.)	Both demand and cost
10 - 12: Food, Beverages and Tobacco	358	144	136	795
13 - 15: Textiles, Apparel and Leather	267	69	57	316
16 - 18: Wood, Paper and Printing	117	27	70	153
20 - 21: Chemicals and Pharma	119	168	123	1045
22 - 23: Rubber and Non-Metallic Minerals	254	109	124	531
24 - 25: Metals	256	70	122	376
26 - 28: Computers, Electrical and Machinery	168	161	72	507
29 - 30: Vehicles and Transport Equipment	44	24	39	69
31 - 33: Furniture, Other Manuf. and Repair	63	77	46	137
Total	1646	849	789	3929

Notes: Summary statistics are for the sample that is used in the decomposition.

When comparing at innovation across industries, it shows that those industries which produce rather homogeneous goods, like the metals, rubber and non-metallic minerals, wood, paper and printing industries do proportionally more cost driven innovation, while for example computers, electrical and machinery industries do more demand driven innovation. Overall, chemicals and pharma are the largest innovating industry, followed by food, beverages and tobacco.

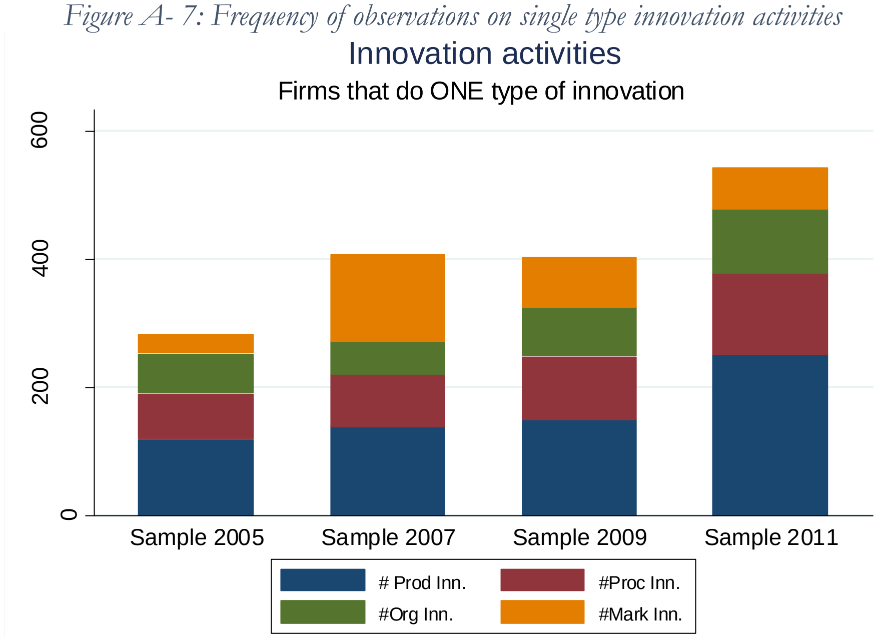
Figure A- 6: Frequency of single versus multiple types of innovation activities



Notes: Summary statistics on the complete CIS sample, similar statistics on the observations that are included in the decomposition analysis can be found in the main body of the paper (table 1).

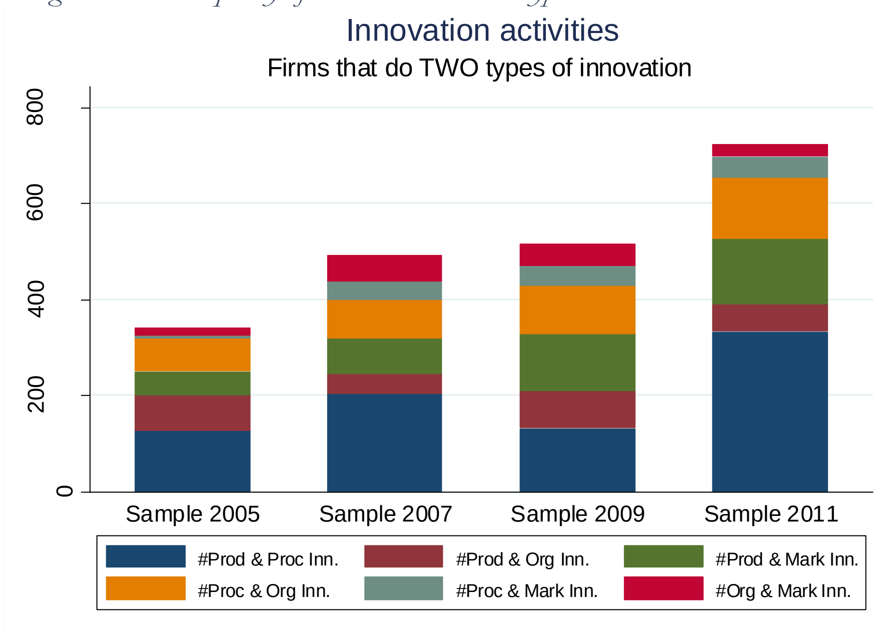
The largest part of our sample of firms is engaged in *multiple* types of innovation at the same time. There are also some firms that do no innovation at all. Given the large share of firms that do multiple types of innovation, we provide further summary statistics on frequencies in the following figures.

Figure A- 7: Frequency of observations on single type innovation activities



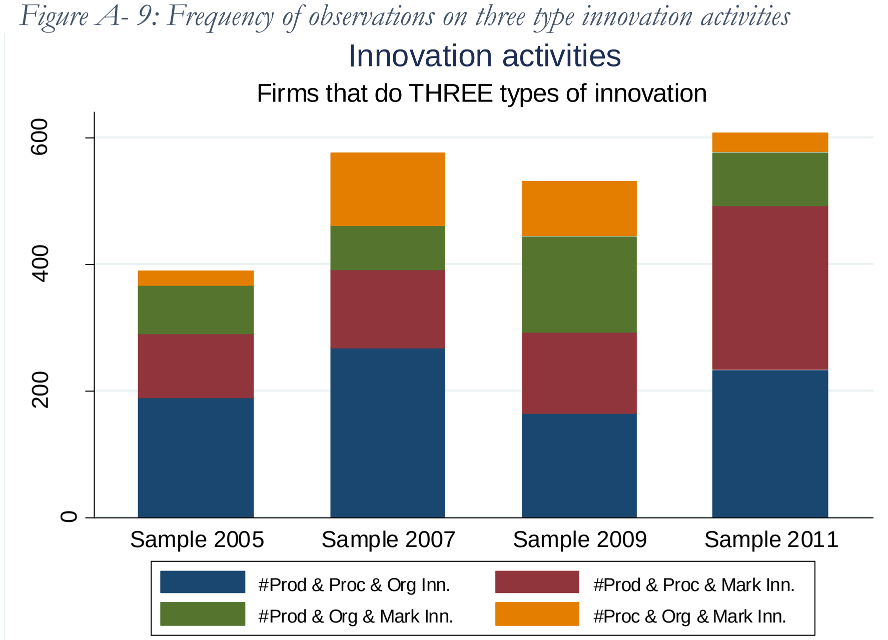
Notes: Summary statistics on the complete CIS sample, similar statistics on the observations that are included in the decomposition analysis can be found in the main body of the paper (table 1).

Figure A- 8: Frequency of observations on two type innovation activities



From figure A-6 it is clear that the majority of firms do multiple types of innovation. The figure above shows more details for those firms that do two types of innovation. The combination product & process innovation occurs most frequently. One reason for this could be that firms try to accomplish a dual competitive advantage, i.e. increasing their productivity by increasing the demand for their products as well as decreasing their marginal costs. Next, product and marketing innovation are often reported simultaneously, this could be firms that focus on increasing firm performance via the demand side of the market. Also, process and organizational innovation are often reported simultaneously, this could be firms that focus on increasing firm performance via the supply side.

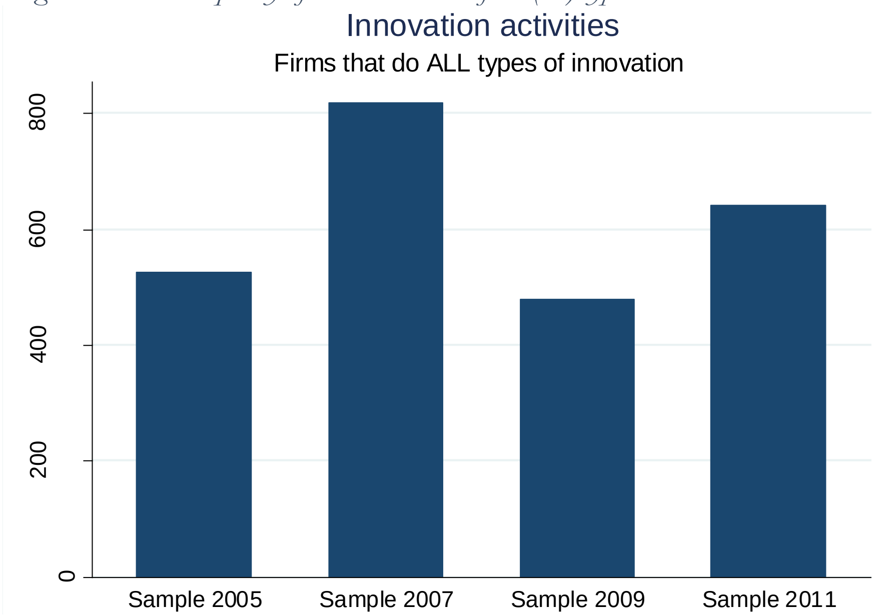
Figure A- 9: Frequency of observations on three type innovation activities



Notes: Summary statistics on the complete CIS sample, similar statistics on the observations that are included in the decomposition analysis can be found in the main body of the paper (table 1).

For firms that do three types of innovation, the combination of product, process and organizational innovation is most frequent. The combination process, organizational and marketing occurs the least frequently simultaneously.

Figure A- 10: Frequency of observations on four (all) type innovation activities



Notes: Summary statistics on the complete CIS sample, similar statistics on the observations that are included in the decomposition analysis can be found in the main body of the paper (table 1).

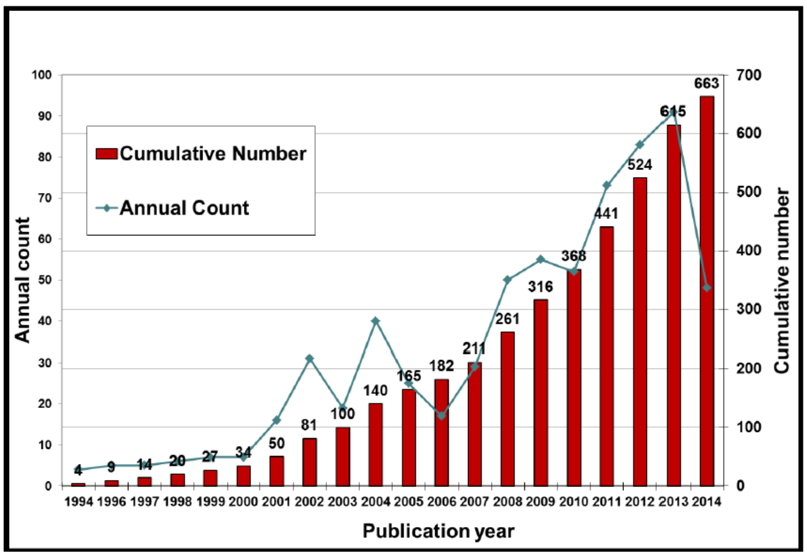
There is a fair fraction that does all types of innovation simultaneously. This behavior seems to be procyclical, in the great recession there were less firms that do all types of innovation.

Appendix C – Datasets

C.1 CIS dataset

The Community Innovation Survey (CIS) is an initiative from Eurostat that is carried out every two years by EU member states. The CIS is a survey of innovation activity in firms, based on the OECD Oslo Manual (1992, 1997, 2005). The purpose is to provide information on the innovativeness and different types of innovations in different industries and for different types of firms. The survey also provides information on various aspects of the development of an innovation, such as the objectives, the sources of information, the public funding, the innovation expenditures etc. The graph below shows the number of published papers that use CIS data. It is fair to say that the CIS is by now an established instrument for research on innovation. In this paper, we rely on the Belgium CIS data that was collected in 2005, 2007, 2009 and 2011. We merge this dataset with the annual account data and the PRODCOM dataset based on the firm's unique VAT number.

Figure A- 11: The CIS data as instrument for measuring innovation



Source: The micro-evidence of innovation: data and research applications, Micheline Goedhuys *UNU-MERIT*, Maastricht, Netherlands

Table A- 8: Questions in the CIS questionnaire

Product innovation	A product innovation is the market introduction of a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems. ▪ Product innovations (new or improved) must be new to your enterprise, but they do not need to be new to your market. ▪ Product innovations could have been originally developed by your enterprise or by other enterprises or institutions. A good is usually a tangible object such as a smartphone, furniture, or packaged software, but downloadable software, music and film are also goods. A service is usually intangible, such as retailing, insurance, educational courses, air travel, consulting, etc.	
	During the three years 200X to 200X+2, did your enterprise introduce:	
	Goods innovations: New or significantly improved goods (exclude the simple resale of new goods and changes of a solely aesthetic nature)	YES (1) NO (0)
	Service innovations: New or significantly improved services	YES (1) NO (0)
Process innovation	A process innovation is the implementation of a new or significantly improved production process, distribution method, or supporting activity. ▪ Process innovations must be new to your enterprise, but they do not need to be new to your market. ▪ The innovation could have been originally developed by your enterprise or by other enterprises or institutions. ▪ Exclude purely organizational innovations – these are covered in section 8.	
	During the three years 200X to 200X+2, did your enterprise introduce:	
	New or significantly improved methods of manufacturing or producing goods or services	YES (1) NO (0)
	New or significantly improved logistics, delivery or distribution methods for your inputs, goods or services	YES (1) NO (0)
	New or significantly improved supporting activities for your processes, such as maintenance systems or operations for purchasing, accounting, or computing	YES (1) NO (0)
Organizational innovation	An organizational innovation is a new organizational method in your enterprise's business practices (including knowledge management), workplace organization or external relations that has not been previously used by your enterprise. ▪ It must be the result of strategic decisions taken by management. ▪ Exclude mergers or acquisitions, even if for the first time.	
	During the three years 200X to 200X+2, did your enterprise introduce:	
	New **business practices** for organizing procedures (i.e. supply chain management, business reengineering, knowledge management, lean production, quality management, etc.)	YES (1) NO (0)
	New methods of **organizing work responsibilities and decision making** (i.e. first use of a new system of employee responsibilities, team work, decentralization, integration or de-integration of departments, education/training systems, etc.)	YES (1) NO (0)
	New methods of **organizing external relations** with other firms or public institutions (i.e. first use of alliances, partnerships, outsourcing or sub-contracting, etc.)	YES (1) NO (0)
Marketing innovation	A marketing innovation is the implementation of a new marketing concept or strategy that differs significantly from your enterprise's existing marketing methods and which has not been used before. ▪ It requires significant changes in product design or packaging, product placement, product promotion or pricing. ▪ Exclude seasonal, regular and other routine changes in marketing methods.	
	During the three years 200X to 200X+2, did your enterprise introduce:	
	Significant changes to the aesthetic **design** or **packaging** of a good or service *(exclude changes that alter the product's functional or user characteristics – these are product innovations)*	YES (1) NO (0)
	New or significantly changed **sales or distribution methods** (such as first use of franchising, distribution licenses, direct sales, new concepts for product presentation)	YES (1) NO (0)

Notes: This table shows the questions that were consistent across the CIS questionnaires of 2005, 2007, 2009 and 2011. Some waives have more questions on marketing innovation, but due to inconsistency across surveys, we do not use these.

C.2 PRODCOM dataset

The ProdCom dataset provides statistics on the production of manufactured goods. *ProdCom* stands for *Prod*ucts of the European *Com*munity. It contains production data for about 3900 products from the mining, quarrying and manufacturing industries (sections B and C of the Statistical Classification of Economy Activity in the European Union, Nace Rev. 2). The survey is mandatory for each industrial firm that employs at least 20 persons or has a revenue of at least 3.928.137 euro in the current or past year. This means that if a firm did employ at least 20 persons at one moment in time during the year, needs to participate to the ProdCom survey the year afterwards. Participating is legally binding by the European Commission Statute 3924/91, the Royal Decree of 28th of January 1994 and the Royal Decree of 20th of February 2008. Each country must report at least 90% of the production of each NACE 4-digit industry, unless the industry represents less than 1% of total production in the economy. During the sample period, there was a change in the classification from both the ProdCom and the NACE classification. We apply the concordance procedure of Van Beveren et al. (2012) for the ProdCom data and use the concordance of the FPS Belgium for concordance of the NACE industry codes at the four-digit level. In this paper, we use the Belgian ProdCom data for the years 2002-2009 and we merge this dataset with the CIS and annual accounts data based on the firms unique VAT number.

The ProdCom dataset is used by Eurostat to obtain an overview on how much of a product is produced in an economy. To avoid double counting, only final goods are accounted for. Production of goods for intermediate purposes is excluded. This is important for our further analysis, because we link this dataset with annual accounts data, in which production expenditures are reported for total production, including both final and intermediate goods production. Therefore, we rescale the production inputs of the annual accounts by the share of final goods sales, which we retrieve from the ProdCom dataset, in total sales, which we retrieve from annual accounts data.

The ProdCom dataset contains for each firm all 8-digit product codes in which it produces. More specifically, the dataset reports for the participating firms for each of these product codes how much is sold as a final good (in units) and the associated turnover of these sales. This allows to obtain a firm specific unit price for each product code. It could be that a firm produces multiple products at different prices within an 8-digit product code. Unfortunately, we cannot capture changes in the product portfolio or price heterogeneity beyond the 8-digit level.

As illustrated in table A-6, the products in the ProdCom dataset are identified with an eight-digit code, of which the first four digits refer to the NACE classification, and the first six digits refer to the CPA classification. The last two digits are created specifically for ProdCom. This information is very useful, as it allows us to assign the different products of multi-product firms to different industries for estimation of the production function and further analysis based on the first four digits of the product code.

Table A- 9: Structure of PRODCOM data

NACE 2digit	NACE 4digit	PRODCOM	Description
10			*Manufacture of food products*
	10.72		*Manufacture of rusks and biscuits; manufacture of preserved pastry goods and cakes*
		10.72.12.57	Waffles and wafers with a water content > 10 % by weight of the finished product (excluding ice cream cornets, sandwiched waffles, other similar products)
		10.72.12.59	Waffles and wafers (including salted) (excluding those completely or partially coated or covered with chocolate or other preparations containing cocoa)