Abstract

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The Impact from Innovation on Productivity: Profitability and Technical Efficiency

B. Cassiman*, J. Konings†, J. Van den bosch‡

May 2018

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JEL codes: D24, L21, O30

Preliminary and incomplete, please do not cite or distribute.

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1. Introduction

Productivity is important both from a business point of view and from a welfare point of view. Innovation is considered to be one of the key determinants of productivity growth. Many studies have indeed shown this to be true, see Hall (2011) and Mohnen and Hall (2013) for survey papers on the literature. However, both innovation and productivity are concepts that are often measured and interpreted in different ways. As described in the OSLO manual (2005), there are four different types of innovation: product, process, organizational and marketing innovation. So far, most of the literature on innovation and productivity focused on product and process innovation. Furthermore, the productivity measures used in the innovation literature are mostly revenue productivity measures, which confound demand and supply side determinants of productivity.

In this paper, we contribute to the literature by building on recent advances of the productivity literature to gain deeper understanding in how innovation impacts the productivity of firms. We move beyond labor productivity and revenue total factor productivity (TFPR) measures that are typically used in this literature. To this aim, we construct a novel dataset for a sample of Belgian manufacturing firms that contains information on innovation activities, traditional firm performance measures, but also on prices and quantities. This dataset allows us to investigate the relation between innovation and several supply and demand components that are comprised in the traditional productivity measures, namely: true technical efficiency (TFPQ), marginal costs, prices and markups. More specifically, we answer the following questions: How can the effect from product, process, organizational and marketing innovation be decomposed into the aforementioned productivity components? How are gains from innovation passed through to the consumer? Are gains from innovation related to the number of products that a firm produces?

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 usually expressed 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, TFP is a revenue residual (TFPR) that confounds true technical efficiency (TFPQ) with market power both in the input and output markets. 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), Goldberg et al. (2016) and Haltiwanger (2016) for a theoretical overview of different TFP measures and how discerning between TFPR and TFPQ can push the literature to a much richer understanding of firm dynamics.

Although it may not be apparent at first sight, the literature on innovation and productivity could highly benefit from these recent advances. Firms that do product innovation often have some form of market power in the output market because of a first mover advantage in their new or improved products or services, which allows them to sell their products or services above competitive prices in a monopolistic

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setting. This would imply that an industry wide deflator underestimates the output price of the firm and hence result in an overestimation of the effect from innovation on TFPR. Similar issues arise for estimating the effect of process or organizational innovation on productivity. Such innovations are typically undertaken to optimize the production process, i.e. reducing the cost per unit produced. The estimated productivity effects from these innovation activities depends on how the firm passes through its gains from innovation to the price of its goods or services. From the trade literature, we know that typically firms do not pass through all gains to the consumer (Amiti, Itskhoki and Konings, 2014). Whether or not this is also true for some types of innovation, is an open question in the literature. These examples illustrate the need for disentangling traditional productivity measures to better understand how innovation affects firm performance.

So far, there is also surprisingly little evidence on the complementarities between different types of innovation in explaining productivity differentials between firms. Although, Carboni and Russo (2018) show that product, process and organizational innovation are interdependent and Polder et al. (2010), find positive effects of product and process innovation when combined with an organizational innovation. According to Hall (2011), the reason for which there is not much evidence on this question, is the existence of collinearity issues when regressing traditional productivity measures on multiple innovation indicators. This makes sense for labor productivity and TFPR, since the incentive for firms to innovate is increasing their turnover and hence TFPR. Hence, it can be hard to identify differential effects of different types of innovation on TFPR. However, not each type of innovation will drive TFPR in the same way, i.e. some types of innovation will likely affect prices and markups, while other types of innovation likely rather affect technical efficiency (TFPQ) and marginal costs. Therefore, it would be interesting to explore whether and how each type of innovation relates to each of the aforementioned underlying productivity measures, which is possible with our data and estimation approach.

Our results suggest that product innovation is associated with lower production, higher marginal costs of which the firm absorbs about 45% itself and passes about 55% through to the consumer. There is no clear effect from product innovation on productivity, and if there is any, it is entirely driven by the price effect. We find no strong effects from process innovation on productivity, but we do find that firms who do process innovation produce more. Furthermore, we find that organizational innovation has substantial positive effects on firm performance. The true technical efficiency of the firm increases when an organizational innovation is introduced, i.e. organizational innovation allows firms to produce more with the same set of inputs. Organizational innovation furthermore has a negative effect on prices and a positive effect on the quantity that a firm sells. The opposite is true for marketing innovation, which we find to be associated with higher prices for the consumer, lower production efficiency and higher marginal costs.

The remainder of the paper is organized as follows. Section 2 describes the empirical framework for estimating the production function, retrieving TFPQ, markups, marginal costs and relating these to product, process, organizational and marketing innovation. Section 3 presents the dataset. The results are presented in section 4. Finally, section 5 concludes the paper.
2. Empirical framework

To understand how innovation affects firm performance, we start from a simple profit equation and show how revenues can be decomposed into the following underlying components: prices, quantities, markups, marginal costs, TFPQ and the composite output. We then relate each of these components to innovation. This permits a rich understanding of the underlying mechanism of the relation between innovation and firm performance.

2.1 Theoretical model

Assume there are no frictions or distortions, so that a firm determines prices and inputs based on simple static profit maximization. Let static profits be given by:

$$\Pi_{ijt} = P_{ijt} \cdot Q_{ijt} - CX_{ijt}$$

(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 of the product. $P_{ijt} \cdot Q_{ijt}$ is the revenue a firm realizes from selling the product, and $CX_{ijt}$ is the cost of the composite input associated to producing the product. To understand the effect from innovation on a firm’s profits, we further decompose this equation, with particular focus on the revenue component because we have unique data on revenues. Take logs of both revenues and costs:

(i) \[ \ln(CX_{ijt}) = c_{ijt} \]

(ii) \[ \ln(P_{ijt}Q_{ijt}) = \ln(P_{ijt}) + \ln(Q_{ijt}) = p_{ijt} + q_{ijt} \]

(2)

Now assume that the production process of a firm can be described by a Cobb Douglas production function of the form $Q = A \cdot L^{\beta_l} \cdot K^{\beta_k} \cdot M^{\beta_m}$.\(^2\) Furthermore, define the markup that a firm charges 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:

(i) \[ p_{ijt} = \mu_{ijt} + m_{ijt} \]

(ii) \[ q_{ijt} = a_{ijt} + \beta_l \cdot l_{ijt} + \beta_k \cdot k_{ijt} + \beta_m \cdot m_{ijt} = a_{ijt} + f(x_{ijt}) \]

(3)

This simple and intuitive decomposition of the profit equation provides us with a rich set of profit determinants. To obtain estimates for $\beta_l$, $\beta_k$ and $\beta_m$, we need to estimate a quantity production function, for which we largely follow De Loecker et al. (2016). In section 2.2 we show how we identify the production function coefficients, taking potential endogeneity in input choices into account. With the estimates at hand, we can obtain $a_{ijt}$, which is the firm’s true technical efficiency in producing the good, or its Total Factor Productivity in Quantities (TFPQ). We follow Syverson et al. (2008) and Haltiwanger

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\(^2\) For the sake of simplicity, we develop the model based on the Cobb Douglas production function. In practice, we will allow for a more flexible production technology, using the Transcendental Logarithmic production function (Christensen, Jorgenson and Lawrence, 1973).
(2016) and define a firm’s revenue productivity (TFPR) as $t f p q_{ijt} + p_{ijt}$. TFPR, which is the residual of the revenue production function, is what earlier studies on the relation between innovation and productivity mostly relied upon.\(^3\) As is clear from our model, TFPR comprises both true productivity and demand shocks. As a result, the exact mechanism on the impact of innovation on productivity cannot be captured from revenue production functions.

To understand how innovation can explain differentials across firms in the aforementioned profit determinants, we run the following set of regressions:

\begin{align*}
(i) & \quad cx_{ijt} = \tilde{\beta}_0 + \tilde{\beta}_{1-4} \cdot \text{Prod; Proc; Org; Mark Innovation}_{ijt} + Z_{jt} + \tilde{\epsilon}_{ijt} \\
(ii) & \quad \begin{cases} 
\hat{\mu}_{ijt} = \tilde{\beta}_0 + \tilde{\beta}_{1-4} \cdot \text{Prod; Proc; Org; Mark Innovation}_{ijt} + Z_{jt} + \tilde{\epsilon}_{ijt} \\
\hat{m}c_{ijt} = \tilde{\beta}_0 + \tilde{\beta}_{1-4} \cdot \text{Prod; Proc; Org; Mark Innovation}_{ijt} + Z_{jt} + \tilde{\epsilon}_{ijt} \\
\hat{a}_{ijt} = \tilde{\beta}_0 + \tilde{\beta}_{1-4} \cdot \text{Prod; Proc; Org; Mark Innovation}_{ijt} + Z_{jt} + \tilde{\epsilon}_{ijt} \\
\hat{f}(x_{ijt}) = \tilde{\beta}_0 + \tilde{\beta}_{1-4} \cdot \text{Prod; Proc; Org; Mark Innovation}_{ijt} + Z_{jt} + \tilde{\epsilon}_{ijt}
\end{cases}
\end{align*}

The dependent variable is always the natural logarithm and the innovation measures are dummies such that the coefficients can be interpreted as the percentage difference in the profit determinant as a result from engaging in the innovation activity. Regression (i) relates innovation to the cost side. Regression set (ii) relates innovation to the revenue side. The vector $Z_{jt}$ is a vector that contains a wide array of control variables: the number of products the firm produces, a firm size indicator, the export status of the firm, a control for competition at the 4 digit level and year and 3-digit industry fixed effects. Cassiman and Golovko (2011) and Cassiman, Golovko and Martínez-Ros (2010) show that exporting firms are typically high productive and that this productivity gain originates from innovation activities. Hence, it is best to control for the export status of a firm when relating innovation to productivity. Furthermore, Aghion et al. (2005) identify a relation between the competition a firm faces and its decision to innovate. Following their approach, we take the four-digit average price cost margin as a measure for competition. This is preferred over indicators such as the market share and Herfindahl concentration index since such indicators strongly depend on the definition of the product market, which is hard to define for Belgian manufacturing firms since the Belgian economy is a small and open economy. The firm size indicator and number of products produced are included to avoid picking up variation in firm size and product scope. Because of the way we set up the model, we can simply add up the coefficients of the micro determinants to gauge the total effects from innovation: $\tilde{\beta} + \tilde{\mu}$ shows the effect from innovation on quantity sold, $\tilde{\beta} + \tilde{\mu}$ the effect from innovation on price, $\tilde{\beta} + \tilde{\mu} + \tilde{\beta}$ the effect from innovation on revenues and $\tilde{\beta} + \tilde{\mu} + \tilde{\beta} + \tilde{\mu}$ the effect from innovation on profits. To the best of our knowledge, we are the first to relate innovation practices to prices and quantities (except for Jaumandreu and Lin, 2016) and to provide a comprehensive decomposition of the relation between innovation and firm performance.

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\(^3\)To the best of our knowledge, no study so far used data on production quantities. Instead, TFP(R) is usually obtained as a revenue residual from regressing a firm’s revenues ($y$) on the production factors, i.e. $y = tf p r + \beta_l \cdot l_{kt} + \beta_k \cdot k_{kt} + \beta_m \cdot m_{kt}$. 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 furthermore ignores the production factors capital and intermediate inputs.
2.2 Empirical approach

Estimating the quantity production function

We obtain estimates for $\beta_l, \beta_k$ and $\beta_m$ by estimating 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 imposes less restrictive assumptions on technology and allows to obtain product-firm specific output elasticities, which is particularly useful since we are interested in markups. The log-linearized Translog production function for our setting is the following:

$$y_{ijt} = \beta_0 + \beta_l l_{ijt} + \beta_k k_{ijt} + \beta_m m_{ijt} + \beta_{ll} l_{ijt}^2 + \beta_{kk} k_{ijt}^2 + \beta_{mm} m_{ijt}^2 + \beta_{lk} l_{ijt} k_{ijt} + \beta_{lm} l_{ijt} m_{ijt} + \beta_{km} k_{ijt} m_{ijt} + \beta_{km} k_{ijt} m_{ijt} + \omega_{ijt} + \epsilon_{ijt}$$

(5)

In which $l, k$ and $m$ refer to employment (measured in full time equivalents), capital (tangible fixed assets) and materials (intermediate inputs). In the case of a revenue production function, $y$ refers to turnover and $\omega$ to TFPR, while in the case of a quantity production function, $y$ refers to quantities and $\omega$ to TFPQ. $\omega$ is the part of output that cannot be explained by the factor inputs, and $\epsilon_{ijt}$ the exogenous error term (e.g. strikes, machine breakdowns). The subscripts $i$, $j$, $t$ refer to product, firm and year. When the dependent variable is expressed in quantities and the independent variables in monetary values, this could result in biased coefficient estimates because of 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 function of the firm’s output price, market share, and product dummies. The reasoning behind this approach is that manufacturing high quality products, and thus expensive products, requires high quality, and thus expensive, inputs. To be internally consistent, we also allow the input prices to depend from 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 $ms_{ijt}$, the quantity production function becomes:

$$q_{ijt} = \beta_0 + \beta_l l_{ijt} + \beta_k k_{ijt} + \beta_m m_{ijt} + \beta_{ll} l_{ijt}^2 + \beta_{kk} k_{ijt}^2 + \beta_{mm} m_{ijt}^2 + \beta_{lk} l_{ijt} k_{ijt} + \beta_{lm} l_{ijt} m_{ijt} + \beta_{km} k_{ijt} m_{ijt} + \beta_{km} k_{ijt} m_{ijt} + w_{ijt}(p_{ijt}, ms_{ijt}, \ln n_{ijt}) + \omega_{ijt} + \epsilon_{ijt}$$

(6)

Having a product specific production function is unusual. In a standard setting, the production function is firm specific. However, we can go beyond this traditional approach since our dataset reports the products a firm produces and for each of these products also the quantity and values that are produced. Specifying the production function this way means that the production technology is assumed to be product specific, instead of firm specific, an assumption that is also made in related work (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 revenue share of the
product within the firm.\footnote{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 the issue of allocating inputs across products is irrelevant, and assign these technology parameters to the products of multiproduct firms. However, our sample size is not sufficient to follow this approach, except for the NACE 25 sector. In appendix we show results for the De Loecker et al. (2016) approach on this industry and compare these with ours.} Furthermore, our innovation measures are also only available at the firm level, hence we need to assume there is a symmetric effect of innovation across products within a firm.\footnote{This assumption could be problematic for product and marketing innovation, which are likely introduced at the product level. 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. For process and organizational innovation, this assumption is less restrictive since these types of innovation is likely to become more useful when firms produce multiple products.} The appendix contains robustness checks based on alternative modelling approaches.

Estimating equation (5) 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 ($\omega$) in function of which it chooses how much labor and materials to use as production inputs.\footnote{Production, and hence also the choice of production inputs, is increasing in $\omega$. Not taking into account unobserved productivity differences results in upward biased $\beta_l$ and $\beta_m$ coefficients when estimating equation (1) 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. As a result, there is no correlation between $\omega$ and $k$, and hence no simultaneity bias on $\beta_k$.} To avoid biases in the $\beta_l$ and $\beta_m$ coefficients, we apply the control function approach introduced by Olley and Pakes (1996).\footnote{Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015) suggest using material inputs instead, i.e. assuming that firms signal their productivity through their materials purchases. However, since we estimate gross output production functions, materials is part of the set of production factors and hence no suited candidate as proxy for productivity.} More specifically, we rely on the insight that investments are monotonically increasing in productivity, conditional on capital. In other words, we assume that firms signal their productivity through their materials purchases. However, since we estimate gross output production functions, materials is part of the set of production factors and hence no suited candidate as proxy for productivity.

In practice, equation (2) is proxied with a higher order polynomial in investments and capital and interactions thereof with a firm’s innovation status. Since capital is both a part of this control function and the set of coefficients that need to be identified in order to obtain $\omega$, Olley and Pakes (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. Again, to be internally consistent, we include last-year’s innovation status in this function, as in De Loecker (2013). This results in the following law of motion for productivity growth:

$$
\omega_{ijt} = g(\omega_{ijt-1}) + \text{inn}_{jt-1} + \xi_{ijt}
$$

(8)
In which $\xi_{it}$ 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 $\xi_{it}$ (Ackerberg, Caves and Frazer, 2015). In Belgium, the labor market is relatively rigid, but materials are flexible inputs and hence the choice of material inputs could be correlated with $\xi_{it}$. We follow Wooldridge (2009) and directly substitute equations (2) and (3) in equation (1) and instrument the materials variables with their lags to avoid the coefficients to suffer from any potential simultaneity bias. The specification we take to the data is the following:

$$
q_{ijt} = \beta_0 + \beta_1 l_{ijt} + \beta_k k_{ijt} + \beta_m m_{ijt} + \beta_{it} l_{ijt}^2 + \beta_{kk} k_{ijt}^2 + \beta_{mm} m_{ijt}^2 + \beta_{tk} l_{ijt}k_{ijt} + \\
\beta_{im} l_{ijt} m_{ijt} + \beta_{km} k_{ijt} m_{ijt} + \beta_{km} l_{ijt} k_{ijt} m_{ijt} + f^{-1}(\text{inv}_{ijt-1}, k_{ijt-1}, \text{inn}_{ijt-1}) + \\
\beta_{im} \text{inn}_{ijt-1} + w_{ijt}(p_{ijt}, m_{ijt}, \text{inn}_{ijt}) + \xi_{it} + \epsilon_{ijt} \tag{9}
$$

$tfp_{ijt}$ can then be obtained from the following equation:

$$
tfp_{ijt} = q_{ijt} - \beta_1 l_{ijt} - \beta_k k_{ijt} - \beta_m m_{ijt} - \beta_{it} l_{ijt}^2 - \beta_{kk} k_{ijt}^2 - \beta_{mm} m_{ijt}^2 - \beta_{tk} l_{ijt}k_{ijt} - \\
- \beta_{im} l_{ijt} m_{ijt} - \beta_{km} k_{ijt} m_{ijt} - \beta_{km} l_{ijt} k_{ijt} m_{ijt} 	ag{10}
$$

**The cost of the composite input**

Profits are the difference between revenues and costs. We only consider the costs 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 times the capital stock. We use a gross fixed capital deflator to obtain the real capital cost. The wage bill and intermediate inputs are deflated using a producer price index.

**Estimating Markups and Marginal costs**

As in Cassiman and Vanormelingen (2013), we rely on the markup estimation approach developed by De Loecker and Warzynski (2012). Under the assumption of cost minimization with regard to a variable input that is free of adjustment costs, it can be shown that the firm will choose the level of this variable input such that the output elasticity of that variable is equal to the input’s cost share. When defining the markup as the ratio of price over marginal cost and imposing the aforementioned assumption on intermediate inputs, it follows that:

$$
\mu_{ijt} \cdot \alpha_{ijt} = \beta_{ijt}^m \Rightarrow \mu_{ijt} = \frac{\beta_{ijt}^m}{\alpha_{ijt}} \tag{11}
$$

In which $\mu_{ijt}$ is the markup of the product, $\beta_{ijt}^m$ the output elasticity of materials that is estimated from equations (9) and $\alpha_{ijt}$ the cost share of materials, which is readily observable from the data. Now, as the markup is defined as the ratio of the price over marginal cost, and since we have the price of the product in our dataset, the marginal cost of the product can simply be obtained from:

$$
MC_{ijt} = \frac{P_{ijt}}{\mu_{ijt}}
$$

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8 Alternatively, we could calculate markups based on the cost share of labor, i.e. the ratio of the wage bill to revenues. However, for labor, the assumption on it being a variable production factor that is free of adjustment cost is unlikely given the system of labor market protection that is in place in Belgium, such as restrictions on hiring, firing and work rules.
3. Data

In order to measure the impact from different types of innovation on a firm’s productivity and further disentangling these productivity effects into profitability and technical efficiency effects, 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. More particularly, we use the CIS 4, CIS 2007, CIS 2009 and CIS 2011 waves. For a discussion on the usefulness of this instrument 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. An overview of the relevant questions can be found in appendix B. Using the information on these questions, the CIS allows us to construct a dummy variables for each type of innovation. Furthermore, we also construct a measure for the export status of the firm from this dataset.

A second dataset we use, is the survey on PRODucts of the European COMmunity (henceforth, ProdCom) of Belgium. This dataset provides production statistics for mining, quarrying and manufacturing firms. From this survey, we obtain information on the number of products a firm produces. More importantly, the dataset also contains for each of these products information on the value and volume of sold production. This also allows us to compute the unit price for each of the products a firm produces.

Next to information on innovation practices (CIS), prices and quantities (ProdCom), we obtain firm level data on production inputs from annual account data of the National Bank of Belgium. All limited-liability firms in Belgium are required to file their annual accounts. 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 intermediate inputs use and depreciation.

Additional deflators for input and output variables were obtained from Eurostat. 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 concording NACE industry codes at the four-digit level. Altogether, when merging the three datasets, we obtain an unbalanced panel dataset of 21,085 product-firm-year for the time span 2002 – 2009 from 14,222 contain all information we need to bring our model to the data.

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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 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.
Table 1 - Summary statistics (in 2005 euros)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Added Value</td>
<td>91,602.246</td>
<td>248,645.421</td>
<td>2,179,103</td>
<td>8,628,828</td>
<td>40,724,273</td>
</tr>
<tr>
<td>Labor Productivity</td>
<td>94,356</td>
<td>73,762</td>
<td>52,036</td>
<td>74,351</td>
<td>113,076</td>
</tr>
<tr>
<td>Tangible Fixed Assets</td>
<td>37,041,693</td>
<td>103,714,495</td>
<td>906,132</td>
<td>3,685,995</td>
<td>19,489,000</td>
</tr>
<tr>
<td>Employment</td>
<td>561</td>
<td>1060</td>
<td>35</td>
<td>116</td>
<td>457</td>
</tr>
<tr>
<td>Number of products</td>
<td>14</td>
<td>22</td>
<td>3</td>
<td>6</td>
<td>14</td>
</tr>
<tr>
<td>Product Innovation</td>
<td>0.64</td>
<td>0.48</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Process Innovation</td>
<td>0.59</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Organizational innovation</td>
<td>0.36</td>
<td>0.48</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Marketing innovation</td>
<td>0.48</td>
<td>0.50</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: Summary statistics of the subsample of our dataset for which we have prices and quantities and can measure TFPQ. The innovation variables show the proportion of product-firm observations that are engaged in innovation. Summary statistics on prices and quantities are omitted because they are not informative across industries.

Table 1 shows some summary statistics from the estimation sample. The summary statistics show that there is substantial heterogeneity in our data. The average firm employs 561 employees, has a capital stock of 37 million EUR and produces 14 products. The median of these variables is lower, indicating that the upper percentiles of the distribution consists of very large firms. As the 25th percentile shows, there are also relatively small firms in our sample. About 64% of the observations reports to do product innovation, 59% process innovation, 36% organizational innovation and 48% marketing innovation.

Table 2: Summary statistics on the number of firms and products in our sample

<table>
<thead>
<tr>
<th>Industry</th>
<th>Share of Sample</th>
<th># Products</th>
<th># Firms</th>
<th># Single Product</th>
<th># Multi product</th>
</tr>
</thead>
<tbody>
<tr>
<td>10: Food Products</td>
<td>13%</td>
<td>207</td>
<td>270</td>
<td>57</td>
<td>213</td>
</tr>
<tr>
<td>11 – 12: Beverages and Tobacco</td>
<td>2%</td>
<td>18</td>
<td>27</td>
<td>17</td>
<td>10</td>
</tr>
<tr>
<td>13 – 15: Textiles, Apparel and Leather</td>
<td>4%</td>
<td>207</td>
<td>160</td>
<td>60</td>
<td>100</td>
</tr>
<tr>
<td>20: Chemicals</td>
<td>36%</td>
<td>357</td>
<td>139</td>
<td>52</td>
<td>87</td>
</tr>
<tr>
<td>21 – 22: Pharma, Rubber and Plastic</td>
<td>4%</td>
<td>119</td>
<td>136</td>
<td>64</td>
<td>72</td>
</tr>
<tr>
<td>23: Non-metallic Mineral Products</td>
<td>3%</td>
<td>50</td>
<td>107</td>
<td>76</td>
<td>31</td>
</tr>
<tr>
<td>24: Basic Metals</td>
<td>18%</td>
<td>70</td>
<td>37</td>
<td>15</td>
<td>22</td>
</tr>
<tr>
<td>25: Fabricated Metal Products</td>
<td>3%</td>
<td>115</td>
<td>211</td>
<td>147</td>
<td>64</td>
</tr>
<tr>
<td>26 – 27: Computers and Electrical Eq.</td>
<td>8%</td>
<td>116</td>
<td>101</td>
<td>63</td>
<td>38</td>
</tr>
<tr>
<td>28: Machinery and equipment</td>
<td>7%</td>
<td>183</td>
<td>129</td>
<td>78</td>
<td>51</td>
</tr>
<tr>
<td>31 – 33: Furniture, Other Manuf. and Repair</td>
<td>1%</td>
<td>45</td>
<td>92</td>
<td>41</td>
<td>51</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>1487</td>
<td>1409</td>
<td>670</td>
<td>739</td>
</tr>
</tbody>
</table>

Notes: Summary statistics of the subsample of our dataset for which we have prices and quantities and can measure TFPQ.

Table 2 shows the share of turnover in total turnover for each industry in our sample, the number of single and multiproduct firms in each industry and the number of different products that these firms altogether produce. The food and beverages, chemicals and basic metals industries have the largest share in turnover. In each industry, with the exception of fabricated metal products, most industries are multiproduct firms. The limited number of single product firms implies that we cannot estimate equation (9) for these single product firms only. Instead, we pool the single and multiproduct firms, allocate inputs to the product level and estimate equation (9) at the product level. The assumption we impose by doing so, is that productivity is firm-product specific, instead of firm specific.
4. Results

We first show our results from the quantity production estimation. Then we discuss how innovation relates to revenues and costs and present the profit decomposition that we designated in section 2.1.

Table 3: Median output elasticities and markups, by sector

<table>
<thead>
<tr>
<th>Industry</th>
<th>$\beta_l$</th>
<th>$\beta_k$</th>
<th>$\beta_m$</th>
<th>RTS</th>
<th>#obs (single)</th>
<th>#obs (multi)</th>
<th>#firms (single)</th>
<th>#firms (multi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10: Food Products</td>
<td>0.18</td>
<td>0.04</td>
<td>0.67</td>
<td>0.92</td>
<td>1.54</td>
<td>1.840</td>
<td>88</td>
<td>1752</td>
</tr>
<tr>
<td>11 – 12: Beverages and Tobacco</td>
<td>0.17</td>
<td>0.24</td>
<td>0.44</td>
<td>0.84</td>
<td>1.62</td>
<td>98</td>
<td>25</td>
<td>73</td>
</tr>
<tr>
<td>13 – 15: Textiles, Apparel and Leather</td>
<td>0.26</td>
<td>0.13</td>
<td>0.63</td>
<td>1.00</td>
<td>1.26</td>
<td>1075</td>
<td>81</td>
<td>994</td>
</tr>
<tr>
<td>20: Chemicals</td>
<td>0.07</td>
<td>0.14</td>
<td>0.78</td>
<td>1.00</td>
<td>0.60</td>
<td>2403</td>
<td>96</td>
<td>2307</td>
</tr>
<tr>
<td>21 – 22: Pharma, Rubber and Plastic</td>
<td>0.29</td>
<td>0.02</td>
<td>0.64</td>
<td>0.98</td>
<td>1.18</td>
<td>727</td>
<td>102</td>
<td>625</td>
</tr>
<tr>
<td>23: Non-metallic Mineral Products</td>
<td>0.30</td>
<td>0.04</td>
<td>0.55</td>
<td>0.88</td>
<td>1.19</td>
<td>453</td>
<td>176</td>
<td>277</td>
</tr>
<tr>
<td>24: Basic Metals</td>
<td>0.43</td>
<td>0.30</td>
<td>0.46</td>
<td>0.80</td>
<td>1.51</td>
<td>324</td>
<td>30</td>
<td>294</td>
</tr>
<tr>
<td>25: Fabricated Metal Products</td>
<td>0.40</td>
<td>0.01</td>
<td>0.50</td>
<td>0.92</td>
<td>1.63</td>
<td>591</td>
<td>179</td>
<td>412</td>
</tr>
<tr>
<td>26 – 27: Computers and Electrical Eq.</td>
<td>0.40</td>
<td>0.04</td>
<td>0.52</td>
<td>0.98</td>
<td>1.45</td>
<td>403</td>
<td>95</td>
<td>308</td>
</tr>
<tr>
<td>28: Machinery and equipment</td>
<td>0.22</td>
<td>0.04</td>
<td>0.69</td>
<td>0.95</td>
<td>0.80</td>
<td>530</td>
<td>64</td>
<td>466</td>
</tr>
<tr>
<td>31 – 33: Furniture, Other Manuf. and Repair</td>
<td>0.49</td>
<td>0.05</td>
<td>0.36</td>
<td>0.90</td>
<td>1.66</td>
<td>491</td>
<td>61</td>
<td>430</td>
</tr>
</tbody>
</table>

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 reports the average markup per industry. Columns 6-8 and 9-11 report the number of observations and firms used for estimating the quantity production function. The number of observations deviates from table 2 because of missing lags for some observations.

Returns to scale are close to one on average, and the output elasticities are on average close to our expectations based on theory and earlier empirical work. The average markup across industries is equal to 1.20, so on average the price for a product is 1.2 times as high as its marginal cost. This is also close to what other authors find. The number of observations in are sample are clearly dominated by the multiproduct firms.

Table 4: Baseline results

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Profits</th>
<th>Revenues</th>
<th>Cost of composite input</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Innovation</td>
<td>-0.0039</td>
<td>0.1496*</td>
<td>-0.4401**</td>
</tr>
<tr>
<td></td>
<td>(0.0595)</td>
<td>(0.0742)</td>
<td>(0.1424)</td>
</tr>
<tr>
<td>Process Innovation</td>
<td>0.0381</td>
<td>-0.0429</td>
<td>0.1929**</td>
</tr>
<tr>
<td></td>
<td>(0.0318)</td>
<td>(0.0337)</td>
<td>(0.0720)</td>
</tr>
<tr>
<td>Organizational Innovation</td>
<td>0.0435</td>
<td>-0.0800***</td>
<td>0.3846**</td>
</tr>
<tr>
<td></td>
<td>(0.0461)</td>
<td>(0.0227)</td>
<td>(0.1163)</td>
</tr>
<tr>
<td>Marketing Innovation</td>
<td>0.0501</td>
<td>0.1341***</td>
<td>-0.1394*</td>
</tr>
<tr>
<td></td>
<td>(0.0577)</td>
<td>(0.0336)</td>
<td>(0.0664)</td>
</tr>
</tbody>
</table>

$R^2$ 0.45 0.70 0.51 0.81

Notes: All dependent variables are in logs and the error structure is robust to heteroskedasticity, autocorrelation and correlation between panels by using Driscoll-Kraay standard errors. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. The regressions include export status, a firm size indicator, the number of products produced, 3-digit industry dummies, year dummies, and a control for competition at the 4-digit level.
Table 4 shows the results for the revenue and cost components of equations (1) and (2) of our model. The data on prices and quantities is readily available in our data, and we refer to the sections 2.1 and 2.2 for how we constructed profits and the cost of the composite input. The empirical focus of this paper is on disentangling the mechanism of how innovation affects the creation of revenues. Yet, our theoretical model also includes costs to show how all adds up to profits, as this is what firms are typically interested in at the end. Innovation seems to have no effects on profits. However, we use the log linear transformation of the dependent variable, and thereby exclude all observations for which the costs of production exceed the revenues. The resulting low number of observations can explain why we do not identify an effect on profits. On the cost side, we find that innovation increases costs. Process and organizational innovation are associated with a 13% higher cost of production, while product innovation is associated with a 5.69% decrease in production costs. Column 3 helps us to understand why this is so. Process innovation and organizational innovation are associated with a large increase in quantity sold, which of course also increases total production costs, while product and marketing innovation lead to a decrease in quantity sold. So the underlying reason of why the production cost decreases with product innovation, is that product innovation is associated with a lower production rate. Marketing innovation increases production costs and decreases the quantity sold, which would make one conclude that marketing innovation is not interesting from the point of view of the firm. However, as column 2 illustrates, marketing innovation is associated with a 14% increase in prices.

Adding columns 2 and 3 shows the net effect of innovation on the revenues of the firm. The price and quantity effects of marketing innovation offset each other, which can explain the literature so far did not establish a relation between marketing innovation and revenues. Product innovation decreases revenues with about 25%, while process innovation and organizational innovation increase revenues with respectively 15% and 30%. These revenue effects are particularly driven by the effect on quantities. From the point of view of the consumer, prices are lower when firms do organizational innovation. On the other hand, prices are about 16% higher when firms do product innovation. This does not necessarily mean that organizational innovation is good and product innovation bad for the consumer. If product innovation is associated with an increase in quality or the creation of a new product variety, this brings utility to the consumer and increases the consumer’s willingness to pay. The combination of a higher price and lower production quantity with product innovation is consistent with quality upgrading or cannibalization of existing products. Using turnover from new products as proxy for product innovation instead of our dummy-measure results in an effect of $-0.1070 (t = -2.89; p < 0.05)$ on quantities and an insignificant coefficient of $0.0151 (t = 0.82, p > 0.05)$ on prices. So when turnover from new products is higher, the overall effects on the sold output is negative, suggesting a cannibalization effect from product innovation. The mechanism of how process and organizational innovation drive revenues and profits is similar: both result in an increase in production costs, an even larger increase in the quantity sold and a negative effect on the output price, although this last effect is not significant with process innovation. The similar mechanism can explain why earlier studies that included both process and organizational innovation found no effects of the latter, as they work simultaneous in driving revenues.

---

11 The effect from innovation is obtained from $100 * \left[ e^{\beta \hat{\beta}_i \hat{\beta}_j / \hat{\beta}_i \hat{\beta}_j} - 1 \right]$. For example, product innovation decreases costs with $100 * \left[ e^{(-0.0586)} - 1 \right] = -5.69\%$. 

12
### Table 4: Profit decomposition

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Marginal cost</th>
<th>Price</th>
<th>Markup</th>
<th>TFPQ</th>
<th>Composite output</th>
<th>Cost composite inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Innovation</td>
<td>0.2687*</td>
<td>-0.1191*</td>
<td>-0.1038</td>
<td>-0.3363***</td>
<td>-0.0586***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1150)</td>
<td>(0.0529)</td>
<td>(0.0837)</td>
<td>(0.0652)</td>
<td>(0.0163)</td>
<td></td>
</tr>
<tr>
<td>Process Innovation</td>
<td>-0.0935</td>
<td>0.0506</td>
<td>0.0327</td>
<td>0.1602**</td>
<td>0.1261**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0999)</td>
<td>(0.0918)</td>
<td>(0.0327)</td>
<td>(0.0494)</td>
<td>(0.0467)</td>
<td></td>
</tr>
<tr>
<td>Organizational</td>
<td>-0.1093</td>
<td>0.0293</td>
<td>0.0674**</td>
<td>0.3171**</td>
<td>0.1258***</td>
<td></td>
</tr>
<tr>
<td>Innovation</td>
<td>(0.0690)</td>
<td>(0.0682)</td>
<td>(0.0274)</td>
<td>(0.1224)</td>
<td>(0.0363)</td>
<td></td>
</tr>
<tr>
<td>Marketing Innovation</td>
<td>0.2288**</td>
<td>-0.0946</td>
<td>-0.0947***</td>
<td>-0.0447</td>
<td>0.0894***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0885)</td>
<td>(0.0669)</td>
<td>(0.0543)</td>
<td>(0.0538)</td>
<td>(0.0234)</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.62</td>
<td>0.35</td>
<td>0.90</td>
<td>0.75</td>
<td>0.81</td>
<td></td>
</tr>
<tr>
<td># observations</td>
<td>14222</td>
<td>14222</td>
<td>14222</td>
<td>14222</td>
<td>14222</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** All dependent variables are in logs and the error structure is robust to heteroscedasticity, autocorrelation and correlation between panels by using Driscoll-Kraay standard errors. All innovation variables are modeled as dummies. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. The regressions include export status, a firm size indicator, the number of products produced, 3-digit industry dummies, year dummies, and a control for competition at the 4-digit level.

Table 4 shows how prices and quantities can be decomposed further, as in equation (3) of our model. Adding up the coefficients of columns 1 and 2 will result in the coefficients in column 2 of table 3, while summing up the coefficients in columns 3 and 4 gives the coefficients from column 3 of table 3. We split the effect from innovation on price into the effect on marginal costs and markups. Not surprisingly, marginal costs are significantly positively affected by product innovations. Product innovations are typically associated with setting up a new production line or changing features of the product, such actions typically increase the marginal costs. The same argument holds for marketing innovation: new labeling or packaging are typically costly, which is also what our data confirms. More surprisingly is that there is no clear effect of process innovation and organizational innovation on marginal costs. One would expect that firms introduce such innovations exactly to lower production costs. While the sign of the effects indeed indicates a decrease in marginal costs from process and organizational innovation, we cannot make a claim on this based on our results. For markups, we only find a negative association between product innovation and markups. As price is defined as the ratio of the markup over marginal cost, this result indicates stickiness of prices: product innovation increases marginal costs, but the firm does not pass this increase in prices through to the consumer, but instead partly absorbs the increase in marginal costs itself, resulting in a lower markup. A back of the envelope calculation would suggest that a firm absorbs 44% ($=\frac{0.1191}{0.2687}$) of the marginal cost increase itself, and passing the rest through to the consumer.

The decomposition of the effects from innovation on the quantity sold shows that the composite output, which is the output generated with production factors labor, capital and materials, strongly decreases with product innovation. This makes sense: when less is sold, less needs to be produced with the input factors. The same can be said for the positive effects from process and organizational innovation on the composite output. What is more interesting, is the effect on TFPQ, which is the true efficiency of the
firm, namely that part of production that cannot be explained by the traditional production factors. The earlier literature in which production functions were estimated to retrieve the productivity of the firm relied, to the best of our knowledge, so far on revenue production functions, in which basically revenues are regressed on production inputs instead of quantities like we do. The consequence is that the revenue residual, which is what the literature calls TFP and we call TFPR, confounds demand and technical efficiency; basically \[TFPR = TFPQ \times P\], or in logs: \[tfpr = tfpq + p\]. When looking at the effects from innovation on the firms true efficiency, we find that organizational innovation is associated with a 7% increase in \(tfpq\) while marketing innovation is associated with a 9% decrease in \(tfpq\). This is an important insight: introducing new methods of organizing work responsibilities and decision making is associated to an increase of about 7% in a firms technical efficiency, or in other words, the introduction of an organizational innovation typically results in an increase in production output with 7% without augmenting any of the other production inputs. From a welfare point of view, this means that organizational innovation should be supported, as it makes us produce more outputs with the same set of inputs. On the other hand, marketing innovation decreases a firm’s technical efficiency, and is as such bad for welfare as it makes firms less efficient.

By adding the coefficients on \(tfpq\) from column 3 in table 4 with those on \(p\) from column 2 of table 3 gives us the impact from innovation on \(tfpr\) and allows us to reconcile our findings with those of the earlier literature. Earlier literature typically found a positive impact from product innovation on \(tfp\), and depending on the country or industry, a positive or negative impact from process innovation on \(tfp\) while there hardly exists any paper on the impact from organizational and marketing innovation on \(tfp\), for a review of the literature we refer to Hall (2011) and Mohnen and Hall (2013). Disregarding that we do not find a significant effect from product and process innovation on \(tfpq\), our findings do provide some insights in why the literature finds no clear evidence on the impact from process innovation: the effect on prices and \(tfpq\) is similar in magnitude, but has opposite signs, thereby resulting in a nearly zero net contribution of process innovation to productivity. For product innovation, the sum of the \(p\) and \(tfpq\) coefficients is about 0.04, which is close to the average coefficient found in earlier research on the effect from product innovation on productivity. Our results show that the positive effect from product innovation on revenue productivity is driven by the price effects.

To be completed

Single vs. multiproduct firms

Small vs. large firms

Old vs. young firms

Complementary effects between different types of innovation
5. Conclusion

In this paper, we contribute to the literature on the relation between innovation and productivity. 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. This rich dataset allows us to build on recent advances of the productivity literature to disentangle revenue productivity effects from innovation into its demand and supply side origins. In a survey paper of the literature on innovation and productivity, Hall (2011) stressed the importance of this caveat. We are not the only ones working on this research questions, also Cassiman and Vanormelingen (2013), Jaumandreu and Mairesse (2010, 2016), Jaumandreu and Sin (2016) and Petrin and Warzynski (2011) contributed on this topic. What distinguishes our paper from earlier work, is (i) the availability of product level prices and quantities, (ii) we develop a decomposition model that allows to dismantle the underlying mechanism on the link between innovation and productivity (iii) while earlier work mainly focusses on product and process innovation, we also investigate organizational innovation, marketing innovation and potential complementarities between different types of innovation.

Our results suggest that product innovation is associated with lower production, higher marginal costs of which the firm absorbs about 45% itself and passes about 55% through to the consumer. There is no clear effect from product innovation on productivity, and if there is any, it is entirely driven by the price effect. We find no strong effects from process innovation on productivity, but we do find that firms who do process innovation produce more. Furthermore, we find that organizational innovation has substantial positive effects on firm performance. The true technical efficiency of the firm increases when an organizational innovation is introduced, i.e. organizational innovation allows firms to produce more with the same set of inputs. Organizational innovation furthermore has a negative effect on prices and a positive effect on the quantity that a firm sells. The opposite is true for marketing innovation, which we find to be associated with higher prices for the consumer, lower production efficiency and higher marginal costs.

All papers come with limitations, and ours is no exception. In theory, the model designated in section 2.1 and section 2.2 allows to investigate how innovation causally affects firm performance. Yet, this would require all variables to be observed at the product-year level. While our data on the output side is rich enough, the data on innovation practices that we use is only collected every 2 years. Consequently, this raises endogeneity issues in the identification. Nevertheless, we are convinced that this paper does contribute to our understanding on the mechanism behind the impact of innovation on productivity and hope that follow up research with more detailed data on innovation practices can alleviate the remaining concerns in our understanding of the impact from innovation on productivity.

12 We need to make the implicit assumption of a symmetric effect of innovation across years and products within a firm. One solution would be to aggregate up all data to the level at which the innovation practices are observed. However, this would be problematic for production quantities of different products within one firm, which is a key variable in our estimation approach. Think about a firm that produces one product in kilograms and another one in liters, adding up production quantities would not make any sense.
References


6. Tables

Table A1: Summary statistics per innovation type - mean

<table>
<thead>
<tr>
<th>Mean</th>
<th>ONE type of innovation</th>
<th>TWO types of innovation</th>
<th>&gt; 2 types of Inn.</th>
<th>No Inn.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor productivity</td>
<td>73.654</td>
<td>75.663</td>
<td>67.786</td>
<td>67.008</td>
</tr>
<tr>
<td>Tangible fixed assets (th.)</td>
<td>5.051</td>
<td>5.694</td>
<td>7000</td>
<td>3.819</td>
</tr>
<tr>
<td>Employment</td>
<td>138</td>
<td>84</td>
<td>144</td>
<td>80</td>
</tr>
<tr>
<td># products</td>
<td>3.84</td>
<td>2.90</td>
<td>2.57</td>
<td>2.65</td>
</tr>
<tr>
<td># single product yes-answers</td>
<td>1232</td>
<td>1259</td>
<td>677</td>
<td>905</td>
</tr>
<tr>
<td># multi product yes-answers</td>
<td>10458</td>
<td>9569</td>
<td>5764</td>
<td>7449</td>
</tr>
</tbody>
</table>

Table A2: Summary statistics per innovation type - median

<table>
<thead>
<tr>
<th>Mean</th>
<th>ONE type of innovation</th>
<th>TWO types of innovation</th>
<th>&gt; 2 types of Inn.</th>
<th>No Inn.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor productivity</td>
<td>63.669</td>
<td>60.970</td>
<td>58.696</td>
<td>55.597</td>
</tr>
<tr>
<td>Tangible fixed assets (th.)</td>
<td>1.167</td>
<td>1.454</td>
<td>1.411</td>
<td>1.066</td>
</tr>
<tr>
<td>Employment</td>
<td>49.8</td>
<td>40.5</td>
<td>50.3</td>
<td>33.6</td>
</tr>
<tr>
<td># products</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

From these tables we learn that firms that do no innovation are clearly smaller, both in terms of firm size as in terms of labor productivity. Firms that do only one type of innovation are smaller than those who do two types of innovation. Within the group of firms that do two types of innovation, we find that all of them are very similar in terms of employment and value added that they create, but interestingly, those that do process and organizational innovation seem more capital intensive.
Table A3: Innovation intensity by number of products produced

<table>
<thead>
<tr>
<th></th>
<th>1 Product</th>
<th>2 Products</th>
<th>3 Products</th>
<th>4 Products</th>
<th>5 Products</th>
<th>6-10 Products</th>
<th>11-20 Products</th>
<th>&gt; 20 products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product innovation</td>
<td>0.44</td>
<td>0.44</td>
<td>0.54</td>
<td>0.59</td>
<td>0.57</td>
<td>0.62</td>
<td>0.70</td>
<td>0.78</td>
</tr>
<tr>
<td>Process innovation</td>
<td>0.45</td>
<td>0.44</td>
<td>0.48</td>
<td>0.49</td>
<td>0.49</td>
<td>0.55</td>
<td>0.66</td>
<td>0.75</td>
</tr>
<tr>
<td>Organizational innovation</td>
<td>0.39</td>
<td>0.36</td>
<td>0.42</td>
<td>0.43</td>
<td>0.37</td>
<td>0.42</td>
<td>0.56</td>
<td>0.61</td>
</tr>
<tr>
<td>Marketing innovation</td>
<td>0.35</td>
<td>0.36</td>
<td>0.39</td>
<td>0.44</td>
<td>0.45</td>
<td>0.40</td>
<td>0.55</td>
<td>0.51</td>
</tr>
</tbody>
</table>

This table shows the ratio of firms that innovate in function of the number of products they make. The more products you produce, the more innovative you are. This holds for all types of innovation. This is similar to the firm size argument, larger firms will produce more products and engage more in innovation.
7. Figures

Figure 1: Frequency of single versus multiple types of innovation activities

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 2: Frequency of observations on single type innovation activities

From those firms who do only one type of innovation, most of them do only product innovation.

Figure 3: Frequency of observations on two type innovation activities
From the previous graphs was 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 seems to be most popular. This could be firms that 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 done together, this could be firms that focus on increasing productivity through affecting the demand side of the market. Also, process and organizational innovation often go together, this could be firms that focus on increasing productivity though affecting their technical efficiency.

Figure 4: Frequency of observations on three type innovation activities

For firms that do three types of innovation, the combination of product and process and organizational innovation is most popular.
There appear to also be firms that do all types of innovation. This behavior seems to be procyclical, in the great recession there were less firms that do all types of innovation.

Figure 6: The number of products produced by firms

Our sample is slightly over 2000 firms. More than 900 of them are single product firms. Only around 50 firms of the sample produce more than 10 products.
Figure 7: Firm size distribution

The x-axis is in logs. Most firms have between $e^2 = 7.5$ and $e^6 = 403$ employees, while the median is around $e^4 = 55$ employees.
Appendix A – Robustness checks

Alternative production function estimation approaches

In the main body of the paper we present results that are derived from estimations of production functions at the product level. This choice is not ubiquitous, but in our opinion probably the way in which the literature will evolve. This is a consequence of the increasing quality of data that researchers have at their disposal. Production functions used to be estimated with industry level data. The last decades, most empirical work relied on production function estimates from firm or establishment level data. In this paper, we can go one step further since we have data at the product level.

However, it may not always be true that more disaggregated is by definition preferred. Indeed, at which level should we actually estimate production functions? This depends on whether production technology is industry specific, firm specific or product specific. Like De Loecker et al. (2016), we assumed that technology is product specific and developed an appropriate estimation procedure based on this presumption. In this robustness check, we will focus on NACE 25, in which we have sufficient single product firms to apply De Loecker et al. (2016).

To be completed
Alternative models

We show for each of the innovation types robustness checks based on earlier literature in this domain. In the main body of the paper, all regressions include export status, competition status and industry and year fixed effects. This section adds to this:

i. Fixed effects estimation.
ii. Use lags of the innovation status instead of current values
iii. Regressions on the subsample of innovating firms, so excluding those that do not innovate
iv. Regressions on the subsample of firms that is not engaged in ongoing innovation at the time of the survey

To be completed
Aggregate prices and quantities

In the main body of the paper, we fully exploit the yearly variation in our dataset on turnover, quantity and prices of products within the firm. Unfortunately, data on production inputs and innovation practices is not available at this disaggregated level. In fact, the data on innovation practices varies only every two years. In order to do the analysis at the product level, the product’s revenue share within the firm is used to allocate inputs across products within the firm. Furthermore, the effect of innovation is assumed to be symmetric across years and products within a firm. In reality, innovation practices are most likely not uniformly distributed across products within a firm, but our data cannot account for this heterogeneity, which leaves us with identifying an average effect of innovation across time and products.

This robustness check shows the results for an alternative approach in which we aggregate up all our data to the level at which the innovation practices change, which is two-yearly at the firm level. This imposes some restrictions as well. In multiproduct firms, the production quantities for some products are e.g. in kilograms while for other products it is in liters. Adding kilograms and liters does not make sense, so for this robustness check we exclude the firms that report in different production units. After doing so, turnover, quantities and production inputs are simply summed over years. Prices are aggregated based on revenue shares of the product. Note that aggregating all data up to the firm level implies that this model will assume productivity to be firm specific.

To be completed
Appendix B – Datasets

CIS dataset: Questions used from the Community Innovation Survey 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) |
| **Service innovations:** New or significantly improved services | 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 organisational 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) |
| New or significantly improved logistics, delivery or distribution methods for your inputs, goods or services | NO (0) |
| New or significantly improved supporting activities for your processes, such as maintenance systems or operations for purchasing, accounting, or computing | YES (1) |

**Organisational innovation**

An organisational innovation is a new organisational method in your enterprise’s business practices (including knowledge management), workplace organisation 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 organising procedures (i.e. supply chain management, business reengineering, knowledge management, lean production, quality management, etc.) | YES (1) |
| New methods of organising work responsibilities and decision making (i.e. first use of a new system of employee responsibilities, team work, decentralisation, integration or de-integration of departments, education/training systems, etc.) | NO (0) |
| New methods of organising external relations with other firms or public institutions (i.e. first use of alliances, partnerships, outsourcing or sub-contracting, etc.) | YES (1) |

**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) |
| New media or techniques for product promotion (i.e. the first time use of a new advertising media, a new brand image, introduction of loyalty cards, etc.) | NO (0) |
| New methods for product placement or sales channels (i.e. first time use of franchising or distribution licenses, direct selling, exclusive retailing, new concepts for product presentation, etc.) | YES (1) |
| New methods of pricing goods or services (i.e. first time use of variable pricing by demand, discount systems, etc.) | NO (0) |
**PRODCOM dataset**

The PRODCOM dataset provides statistics on the production of manufactured goods. The term stands for PRODucts of the European COMmunity. 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 2). The PRODCOM initiative originated from a cooperation between the members of the European Community to improve statistical comparability of industrial production. 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. 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.

The products are included in PRODCOM according to their eight-digit code, for which the first four digits of a PRODCOM code refer to the NACE classification, and the first six digits refer to the CPA classification. The last two digits are created specifically for PRODCOM.

**Annual accounts dataset**

*To be completed*