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Closing the Gap: An Empirical Evidence on Firm's Innovation, Productivity, and Exports

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Abstract

It is well known that exporters are productive firms. But the source of their productivity is left unexplained. This paper aims to endogenize the productivity heterogeneity of exporting firms by incorporating innovation in a structural model framework. In doing so, we close the gap between the innovation-productivity and productivity-export literature. Two waves of Swedish Community Innovation Survey (CIS) are merged. This allows for a setup that takes into account the links from innovation input to innovation output and also from innovation output to productivity and exports. The main findings highlight that exporters are productive firms with innovation output in the past, which in turn was driven by prior R&D and other innovation activity investments.

Keywords: innovation, productivity, export, firm-level, structural model, community innovation survey

JEL: C31, L60, O31

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1. Introduction

Exporters are known to be a selected group of productive firms. They can afford the associated upfront fixed costs of entering the foreign markets. In other words, they succeed in crossing the *productivity threshold* and *self-select* themselves into exporting (Bernard & Jensen, 1999; Bernard & Wagner, 1997; Delgado, Fariñas, & Ruano, 2002; Melitz, 2003). This self-selection literature has been an important theoretical foundation for many recent empirical trade studies, mainly due to its prediction that is in line with the observed data. Besides being more productive, exporters are a bigger-sized minority among firms – a stylized fact that Eaton, Kortum, and Kramarz (2004) observe for French manufacturing firms.[1] However, the literature is still in its development stage and the existing evidence often provides a mixed picture. For example, the direction of causation between productivity and exporting is still an unresolved debate. The self-selection literature often treats firms' productivity as being assigned from a random draw, thus it is exogeneous to the firm and remains a "black box" in the model. So the question is: Where does the heterogeneity of firms' productivity come from?

Several explanations attribute a gain in productivity to the firm's innovation-related activities, the argument being that a firm decides to invest in R&D and related activities to improve their operations. The result of a successful investment in these activities is likely to increase the productivity and firms' performance. Ederington and McCalman's (2008) dynamic model introduces the difference in adoption rates of new technologies (or innovation) as the primary source of productivity heterogeneity. Segerstrom and Stepanok (2011) model firms' R&D as either traditional quality improvement activities or investments for becoming exporters. Similarly, if we look at another strand of literature, namely micro-studies of innovation, it is found that the main source of the productivity heterogeneity is firms' investments in R&D and other innovation activities that lead to innovation output of the firm.[2] The production function framework, advocated by Griliches (2000), and recently the endogenous growth model (P. Aghion & Howitt, 1992; Romer, 1990) attribute productivity gain to the firm's capital accumulation and technological change (or innovation). Despite the innovation being a possible answer to the question we posed above, the studies that attempt to examine this are still rare.[3]

This paper investigates the source of firms' productivity by examining the link from R&D investments and innovation output to firms' productivity and export performance. In doing so, we aim to close the gap between the self-selection (productivity-exporting) and innovation-productivity literature. The empirical evidence in this paper comes from the modified structural model that extends the framework by Crépon, Duguet, and Mairesse (1998) and (Lööf & Heshmati, 2006). Empirically, we employ two waves of Sweden's Community Innovation Survey (CIS)

[1] Other studies have found the same pattern. See a review by Wagner (2007) for such studies.
[2] The recent studies are based on innovation survey data. For a review, see Hall and Mairesse (2006).
[3] Antonietti and Cainelli (2011); Aw, Roberts, and Xu (2008); Aw, Roberts, and Xu (2011) are some exceptions.

and complement with detailed data on firm-level characteristics and exports. The structural setting gives us the flexibility to interact the innovation, productivity, and firms' exports. Moreover, we are able to deal with several econometric issues, namely the selectivity, simultaneity, and endogeneity problems.

Because not all firms invest in R&D and other innovation activities, excluding the non-innovative firms from the estimation will give rise to the selectivity problem. While allowing the interaction between innovation, productivity, and export performance, we are able to deal with the simultaneity issue, since it is argued that exporting can also raise firm's incentives to innovate (Long, Raff, & Stähler, 2011). The dynamic nature of innovation process involves a lag time, thus disregarding it will result in the endogeneity problems. We will discuss more in details later.

Our main contribution is twofold. First, this study is relevant to the debate on firms' innovative activity by providing a detailed empirical analysis using comparable CIS data to support the argument. From a policy perspective, on the other hand, including the export equation in our extended structural model provides an insight into the internationalization of firms and how innovation policies might be able to increase the competitiveness of the economy.

The rest of this paper is organized as the following: section 2 provides a relevant theoretical framework. In section 3, we introduce the structural model as an empirical strategy and discuss about econometric issues. Section 4 presents the data and descriptive statistics. The results and discussion are in section 5, and the last section concludes the paper.

2. Conceptual framework

2.1 Productivity – Exporting

Not all firms engage in exporting activities. Eaton, Kortum, and Kramarz (2004) find that among French manufacturing firms, exporters are a minority that tends to be more productive and larger than nonexporters. One of the main export barriers are the entry costs. These costs can be variable, with a standard "iceberg" assumption (Bernard, Eaton, Jensen, & Kortum, 2003), or fixed (Melitz, 2003; Roberts & Tybout, 1997).

The variable costs are assumed to consist mainly of the transportation and tariffs, in which they vary with the amount of export shipment and the distance to the destination. The fixed costs are the initial costs that each firm invests to obtain a permit, establish the distribution network and various other transaction costs. During the latter half of the twentieth century, the variable costs have seen a decline due to advances in technology and trade liberalization. This implies the growing importance of informal trade barriers which constitute the upfront fixed costs.

Ample empirical evidence connects exporters with higher productivity compared to nonexporters. Wagner's (2007) survey concludes that, among 54 studies covering 34 countries, "exporters are found to be more productive than nonexporters, and the more productive firms self-select into export markets."

Among all firms, only those at the upper end of the productivity distribution can afford these costs of entering the foreign markets. But the initial productivity of each firm and the productivity distribution is exogenously determined (Melitz, 2003) or depend only on the variation of the firms' efficiency (Bernard et al., 2003). The theories developed thereafter have largely neglected it and thus the source of productivity gain remains a "black box," until recently.

There are attempts to formally model firm's exports with the endogenous productivity. Ederington and McCalman (2008) develop a dynamic model with endogenous firm-level productivity by using an adoption of new technology to explain the heterogeneity in firms' productivity. In this model, the difference across firms is the timing of adoption due to the high cost, albeit marginally decreasing, of early technology adoption.

Segerstrom and Stepanok (2011) propose a quality-ladders endogenous-growth model without Melitz-type assumptions that firms invest in R&D to introduce new varieties of products. Instead, they distinguish two types of R&D technologies: inventing a higher quality of existing products, and learning how to export. The latter involves an investment in terms of stochastic fixed market entry costs. Compared to Melitz (2003), the productivity threshold does not exist in this setting and there is an overlap of the productivity distribution between exporters and nonexporters. The difference between this quality-ladders model and the model by Ederington and McCalman (2008) is that each product requires a different level of R&D. It is, therefore, more difficult to invest in R&D and learn how to export complex and highly advanced products. Restated, it is the difference in product quality versus the difference in timing of technology adoption.

Other recent theoretical papers have also introduced R&D and innovation to provide a structural link with firms' decision to export. In this strand of literature, firms make a joint decision to export and investment in R&D, in which this investment raises firms' productivity and affects positively on exporting while participation in the export market also raises the return to R&D investments. The evolution of firms' productivity is characterized as a stochastic process. Starting from the exogeneous productivity in Olley and Pakes (1996), there are extensions to allow the evolution of productivity endogeneously with R&D (Doraszelski & Jaumandreu, 2013), product and process innovations (Peters, Roberts, Vuong, & Fryges, 2013), and exporting (Aw et al., 2011; Maican, Orth, Roberts, & Vuong, 2013). Using this framework, the empirical evidence confirms the significant role of R&D investments in the evolution of productivity dynamics and exports among Taiwanese firms (Aw, Roberts, & Winston, 2007; Aw et al., 2008; Aw et al., 2011).

2.2 Innovation – Productivity

The innovation effect on productivity is well documented empirically (see Cohen, 1995; Griliches, 2000 for some surveys), and several theoretical models have proposed the idea that firms may invest in R&D to increase the productivity before entering foreign markets.

The endogenous growth theory provides an early foundation that links economic output and innovation (P. A. Aghion, Howitt, Brant-Collett, & Peñalosa, 1998; Howitt, 2000; Romer, 1990). In a similar view, firms' accumulation of technological capabilities is considered as one of the key sources of productivity advantages (Castellani & Zanfei, 2007). Firms with better technologies are able to increase profit margin and reduce prices, thus increasing the competitiveness (Cantwell, 1989, among others).

The change in work practice, the choice of production inputs, and better managerial ability are also argued to be an important factor contributing to an improvement of firms' productivity. Schmitz Jr (2005) points that firms are more likely to adopt a new technology and gain higher productivity in a competitive environment, such as the international markets, than domestic firms. Castellani and Giovannetti (2010) find that the productivity differences (or *premia*) among Italian firms vanish when high-skilled knowledge-intensive workers and the differing returns on capital and labour are accounted for.

Klette and Kortum (2004) develop the theoretical model to link firms' heterogeneity, R&D, and productivity based on several stylized facts from empirical studies on the subject. In this model, the heterogeneity of productivity is derived from a variation in the size of innovation steps. The model predicts that R&D intensity is positively correlated with persistent differences in productivity across firms.

Accordingly, the empirical evidence is growing, using the knowledge-production framework in microlevel studies of innovation, and shows that innovation indeed leads to higher productivity within firms across countries (Hall & Mairesse, 2006). This knowledge-production framework argues that innovation itself should be treated as a process with input and output parts. The empirical evidence suggests that innovation input increases innovation output and eventually it is innovation output that increases productivity (Crépon et al., 1998). So we base our analysis on the distinction between innovation input and output, which is considered vital for empirical innovation studies.

There is a consensus in the literature that innovation input stimulates innovation output. This can be discussed by referring to a stream of literature on the "two faces of R&D," which shows that not only R&D (or innovation input, in general) stimulates innovation output, but also R&D can facilitate the imitation of other discoveries by increasing the absorptive capacity (Griffith et al, 2004). The first face of R&D is rather an older argument, dating back to at least the Knowledge Production Function framework, which provides evidence that R&D investment stimulates an introduction of various measures of innovation at the firm level (Griliches, 1963, 1979, 1990). The second face of R&D is a more recent argument, which refers to the argument on the positive effect of the absorptive capacity of a firm (or the knowledge capital of firm) on firms' imitative capacity and eventually innovation (Cohen and Levinthal, 1990; Klette and Kortum, 2004). Quantitatively, innovation input has traditionally been measured as R&D investment (Griliches, 1998), but more recent innovation surveys have added more categories, such as investment in training of employees (OECD, 2005). Such addition of more categories to innovation input is important, since, for instance, it is shown that R&D investment accounts for only about one quarter of the total innovation input expenditure in Dutch firms (Brouwer & Kleinknecht, 1997). In this paper, we incorporate the term innovation input to encompass all the categories of innovation-related activities.

Innovation output has traditionally been measured in terms of patents or even productivity (Klette & Kortum, 2004), while recent innovation surveys, following Schumpeter (1934), have provided more direct measures of innovation output, grouped in several types: product, process, marketing, and organisational innovation (OECD, 2005). In particular for the product innovation, an attractive measure has been available – i.e. the amount of firms' sales due to innovative products – which is argued to have fewer weaknesses compared to classic measures (Kleinknecht, Van Montfort, & Brouwer, 2002).

Using this quantitative measure of innovation output, we can plot in Figure 1 the distribution of productivity of all Swedish firms in this study. The thick solid line representing innovative firms is vertically above the dashed line of noninnovative firms at the upper end of the productivity distribution, to the right of the horizontal axis. This implies that, among all firms, innovative firms are those that appear more concentrated, i.e. having a higher density, at the upper end of the productivity distribution.

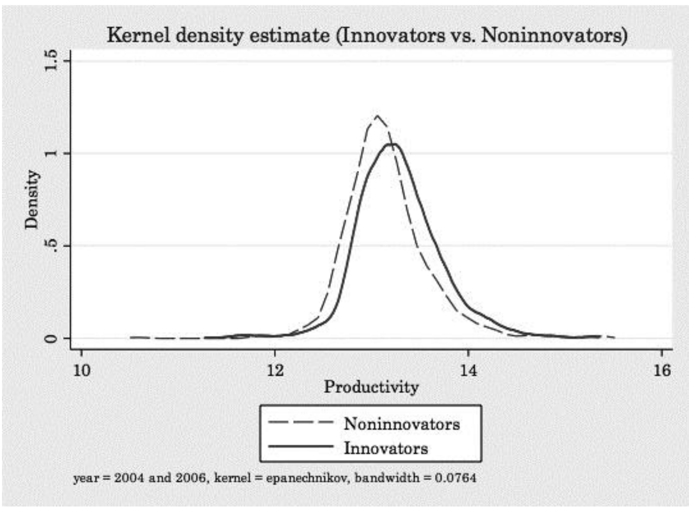

Figure 1: Kernel distribution of productivity between innovative vs. noninnovative firms, 2004 and 2006

In summary from the discussion above, we can establish two hypotheses as:

HP1: Export performance is driven by the productivity of the firm.

HP2: The productivity is, in turns, associated with innovation output.

The next section presents an outline of the empirical strategy in order to test our hypotheses.

3. Empirical strategy

3.1 Models of innovation, productivity, and exports

Most studies test the relationship of innovation and firms' performance using R&D investments as a proxy for innovation. Although related, R&D investments are merely a part of innovation input. This input is the total innovation investment which, according to the Oslo manual, consists of six innovation investment categories: intramural R&D, extramural R&D, machinery acquisition, other external knowledge gathering, training, and market introduction of innovation (OECD, 2005). To assess the impact of innovation on firms' performance, the focus must be placed on the outcome of the knowledge production, which is the output of these innovation activities. Therefore, it is crucial to distinguish innovation into input, consisting of R&D and other related investments, and output, as a successful result of such input. The innovation output can be measured accordingly as the fraction of total turnover due to innovative products.[4]

The empirical setting that allows for the distinction above can be traced back to Pakes and Griliches (1984), who introduce a knowledge-production function that can be written in its simplest form as $\dot{k} = \sum r + u_1$, $p = \dot{k} + u_2$, and $a = \sum r + u_3$, where $\dot{k}$ denotes knowledge increment, r is the expenditure in different research activities, p is the number of patents as inventive output, and u_i are the error terms assumed to be independent in all three equations. This setup disentangles the relationship between innovation input (captured by the knowledge increment variable) and productivity by providing an intermediate step, that is the innovative output (measured as the number of patents). However, this set of equations suffers from an important econometric issue. Because the firms that enter the estimation are not randomly drawn from the whole population, the selection issue can arise and bias the resulting estimates. Moreover, because the innovation input is endogeneous in the innovation equation and the innovation output is endogeneous in the productivity equation, this can also lead to a simultaneity bias.

The seminal work of Crépon et al. (1998) (CDM hereafter) highlights these selectivity and simultaneity issues and solves the selection bias by introducing a selection

[4] Innovation output is further divided into new to the firm and new to the market. In this study, the focus is on the former and not necessarily the latter.

equation in addition to the three-equation approach above and assuming the disturbance terms to be correlated across all four equations. Using an asymptotic least squares estimator, they provide a consistent estimate that corrects for both issues.

Lööf and Heshmati (2006) use a structural model that differs slightly from the CDM model. Instead of assuming all disturbances to be correlated, they separate the four equations into two parts – the selection equations (using the Heckman selection estimator) and the innovation-performance equations (using three-stage least squares; 3SLS).

The setup can be formulated as:

$$g^* = \beta_{0,1} + \sum_n \beta_{n,1} x_{n,1} + \varepsilon_1 \quad (1)$$

$$k^* = \beta_{0,2} + \sum_m \beta_{m,2} x_{m,2} + \varepsilon_2 \quad (2)$$

$$i = \beta_{0,3} + \beta_k k + \beta_{IMR} IMR + \sum_l \beta_{l,3} x_{l,3} + \varepsilon_3 \quad (3)$$

$$p = \beta_{0,4} + \beta_i i + \beta_e e + \sum_j \beta_{j,4} x_{j,4} + \varepsilon_4 \quad (4)$$

where the selection part contains g^* denoting innovation input propensity (a latent variable with value 1 if total innovation investment is positive) and k^* denoting innovation input intensity (logged total innovation investment per employee) which corresponds to the observed innovation input propensity – i.e., g = 1 – and the last two equations consist of the innovation output and productivity, denoted i and p. In this case, the disturbances from equations (1) and (2) are correlated, as are equations (3) and (4). The two parts are linked by IMR – the inverted Mills' ratio from the selection equations in the previous step.

In Antonietti and Cainelli (2011), they investigate the role of spatial agglomeration in an extended model that involves the research equations, innovation output propensity, productivity, and export propensity. The five-equation structural model can be written as:

Research equations: $$g^* = \beta_{0,1} + \sum_n \beta_{n,1} x_{n,1} + \varepsilon_1 \quad (5)$$

$$k^* = \beta_{0,2} + \sum_m \beta_{m,2} x_{m,2} + \varepsilon_2 \quad (6)$$

Innovation equation: $$\Pr(i = 1 | X = x_l) = \Phi(\beta_{0,3} + \beta_k k + \sum_l \beta_{l,3} x_{l,3} + \varepsilon_3) \quad (7)$$

Productivity equation: $$p = \beta_{0,4} + \beta_i i + \sum_j \beta_{j,4} x_{j,4} + \varepsilon_4 \quad (8)$$

Export equation: $$\Pr(e = 1 | X = x_s) = \Phi(\beta_{0,5} + \beta_p p + \sum_s \beta_{s,5} x_{s,5} + \varepsilon_5) \quad (9)$$

where $\Pr(i)$ and $\Pr(e)$ denote the propensity of innovation output and exports, respectively. In this setup, the innovation equation (7) does not include the inverted

Mills' ratio from the research equations, (5) and (6), and the correlation of the error terms across equations is not assumed.

The analysis in this study resembles the structural model by Lööf and Heshmati (2006) in equations (1) to (4), with an additional equation for the export performance, measured as logged export value per employee:

$$e = \beta_{0,5} + \beta_p p + \sum_s \beta_{s,5}\, x_{s,5} + \varepsilon_5 \tag{10}$$

3.2 The full model

The full model consists of the total of five equations: the innovation input equations (1) and (2), the innovation output equation (3), the productivity equation (4), and the export performance equation (10).

Equation (1) examines the decision of the firm to invest in innovation input. Here, $x_{n,1}$ is a vector of the independent variables explaining the decision of the firm to invest in innovation. These variables include firm size (measured as logged number of employees), physical capital (logged sum of building, machinery, and inventories), human capital (fraction of highly educated employees, with at least three years of university studies), and ownership structure variables (categorical variables indicating a firm as being non-affiliated, part of a uninational corporate group, domestic MNEs, or foreign MNEs).[5] The non-affiliated firms are the reference group. These explanatory variables mainly capture the core characteristics of firms in terms of internal resource allocation (size and physical capital) and knowledge capacity building (human capital). The corporate affiliation aims to differentiate the ownership structure among firms, in which multinationals are more likely to engage in R&D activities than firms that only serve domestic market. All variables are expected to exhibit positive coefficients.

Equation (2) considers the amount of total innovation investment. Again, $x_{m,1}$ is a vector of explanatory variables, which is the same as $x_{n,1}$ except $x_{m,1}$ does not include firm size.[6] To provide consistent and more robust estimates, we follow the general practice of variable exclusion from the outcome equation. This means that the excluded variable is expected to be correlated with the probability of investing in R&D-related activities, but not with R&D intensity. Because one of the stylized fact

[5] This categorical variable for ownership structure is a registered data obtained from Statistics Sweden. We prefer using this categorical variable to a dichotomous variable in CIS data indicating whether a firm belongs to a group or not. This type of substitution is argued to be useful for improving the quality of an empirical analysis in CIS data (Mairesse & Mohnen, 2010).

[6] Unfortunately, the data does not allow us to construct the market share variable, which is common in the study of this kind (see how to construct the variable in Crépon et al. (1998)). It is expected to be positively related to R&D.

among innovation studies indicates that R&D intensity is independent of firm size (Klette & Kortum, 2004), so we drop firm size from equation (2).

Then, equation (3) explains the innovation output of the firm. This equation is also called the *innovation production function*. The predicted value of innovation input from the previous equation (k) is used as one of the regressors. A vector of explanatory variables, $x_{l,3}$, determines innovation output and includes similar variables as $x_{n,1}$ with an addition of Cooperation variable, indicating whether a firm has any formal cooperation agreements with external parties or not. This cooperation variable aims to capture the external factor of innovation outside the firms that can contribute to the successful investments in innovation. The *IMR* variable is the inverted Mills' ratio, used to correct for selection bias (Heckman, 1979), and is expected to show a statistically significant result. Here, the error term is assumed normal.

Equation (4) explains firms' productivity. The predicted value of innovation output from the third equation (i) is used as a regressor. Similarly, $x_{j,4}$ include the same variables as $x_{n,1}$. The error terms in equations (4) and (5) are assumed to be correlated, when we estimate the two equations jointly by the Three-Stage Least Squares (3SLS) estimator. Export intensity (e) is used as a simultaneous explanatory variable to allow for an interaction between productivity and exports. The inclusion of an export variable can capture firm's learning from previous exporting to become more productive in later periods (Andersson & Lööf, 2009; Clerides, Lach, & Tybout, 1998).

Eventually, equation (10) explains the export performance. The $x_{s,5}$ vector of explanatory variables include, in addition to $x_{j,4}$, firms' productivity and previous export experience. Following the self-selection literature, we would expect productivity to exhibit a positive and significant result which corresponds to a greater engagement in export markets of productive firms. The experience variable is included to distinguish firms that already paid upfront fixed entry costs previously from new exporters.

3.3 Model estimation

In this paper, we employ two alternative estimation strategies in order to test the relationship between innovation input, innovation output, productivity, and exports within the structural framework above. The first and preferred strategy is a three-step procedure. The second strategy is a two-step procedure. We compare these two alternative strategies at the end of this section and present the results for the two-step approach in the Appendix. The three-step procedure can be described as follows:

Step 1: Innovation Input's determinants (Generalized Tobit model)

In this step, we estimate innovation input equations, equations (1) and (2), simultaneously by the Generalized (Type-2) Tobit, or sometimes called Heckman selection model (Heckman, 1979). Because some firms that participate in the CIS survey do not report their innovation activity investments; hence the dependent variable is missing for these firms. Also these missing values are *not* random, which imply that there is a potential selection bias in the CIS data (Mairesse & Mohnen, 2010). The Heckman model is designed to handle such potential selection bias (Heckman, 1979). This implies that equation (1) is the selection equation in which the innovation input propensity is the dependent variable. The outcome equation is, therefore, equation (2) and the innovation input intensity is the dependent variable. We use the Full-Information Maximum Likelihood estimator (FIML) to jointly estimate the two equations. Alternatively, we could estimate them separately as a two-step procedure, with the first being probit, and the second being Ordinary Least Square (OLS) with the inclusion of the inverted Mills ratio in the second step. However, Verbeek (2008) shows that the first approach is superior to the two-step approach in terms of consistency and efficiency.

Step 2: Innovation Input to Innovation Output (OLS)

In this step, we estimate innovation production function, equation (3), using OLS. The choice of the estimator is in line with recent advancement in estimating the knowledge production function, which does not assume an interaction between innovation output and productivity, leaving OLS as a safe estimator (Mairesse & Robin, 2012). From the first step, we use the lagged predicted value of the dependent variable, namely the innovation input intensity (of year 2004), as one of the main independent variable in this step to explain innovation output (in 2006). There are three reasons for this: (i) in order to link step 1 with step 2 as part of the structural model (ii) in order to reduce the potential endogeneity problem by replacing the observed value of innovation input with its predicted value as an instrument[7] (iii) in order to reduce reverse causality and endogeneity problems by using the two-years lag of the main independent variable (innovation input in 2004) to explain the dependent variable (innovation output in 2006).[8] Standard errors are bootstrapped to correct for the bias induced by an inclusion of the predicted regressor (Antonietti & Cainelli, 2011; Mairesse & Robin, 2012).

An important issue is that this step limits the observations to a subsample of innovative firms (378 firms), since we are seeking to explain the innovation output "of innovative firms." Innovative firms are defined as the firms which have positive innovation input (total investment in innovation activities) and positive innovation

[7] The main explanatory variable for innovation output is innovation input (intensity). However, this variable is argued to be potentially an endogenous variable, since unobserved characteristics could increase both firms' innovation input efforts and its innovativeness (Mairesse & Robin, 2012; Mohnen, Mairesse, & Dagenais, 2006). Furthermore, it is suggested that predicted value (instead of observed value) can act as an instrument and reduce endogeneity problem (Lööf & Heshmati, 2006; Mairesse & Robin, 2012).

[8] There are good reasons to believe that innovation input (investments) takes time to exhibit its effect on innovation output (innovative sales). Studies using 'patent' usually use 2 or 3 years lag between innovation input and output (Fritsch and Slavtchev, 2007; Ponds et al, 2010). However, CIS studies seldom have considered such lag structure, due to the cross-sectional nature of CIS data. Nevertheless, thanks to merging the two waves of CIS, this paper is able to use the lag in the analysis.

output (innovative sales) (Lööf & Heshmati, 2006). However, this may cause a selection bias, since the total sample is reduced to the non-random subsample of innovative firms (Crépon et al., 1998; Lööf & Heshmati, 2006). In order to deal with the selection bias, we include the inverted Mills' ratio variable calculated from the first step as an additional regressor in this step.

Step 3: Innovation Output to Productivity & Export (3SLS)

In the third and final step, we simultaneously estimate productivity and export equations, equations (4) and (5), using the Three-Stage Least Square estimator (3SLS).[9] There are two reasons for the chosen estimator: (i) in order to deal with the simultaneity problem, and (ii) in order to allow for an interaction between productivity and export to test for the two non-mutually exclusive relationships concerning productivity and exporting, namely self-selection versus learning-by-exporting. An alternative estimator is Two-Stage Least Square (2SLS), but 3SLS has a higher efficiency advantage over 2SLS by taking into account the correlation of the error terms between equations (Greene, 2003). We use the lagged predicted value of the innovation output from the previous step as an independent variable (in 2006) to explain subsequent productivity. The logic is the same as the three reasons for including predicted innovation input to explain innovation output, provided in step 2.

An alternative strategy for the three-step procedure is a 2-step procedure. The first step in the two-steps procedure is the same as above. In the second step of the two-step procedure, we allow for an interaction between innovation output, productivity, and export *altogether* (the result is reported in Table 6 in the Appendix). We prefer and employ the three-step approach for the main findings in this paper. This is because the three-step procedure has an additional lag structure – not only from innovation input to innovation output, as in the two-step procedure, but also from innovation output to productivity and exporting. In this way, we allow for the timing of innovation output to affect firms' performance and, additionally, the problem of endogeneity and reverse causality can be substantially reduced.

The main difference between the three- versus two-step procedure is that in the three-step procedure, the predicted values from the steps 1 & 2 are included as independent variables in the succeeding steps, 2 & 3, to reduce the simultaneity bias. The lagged structure of the independent variables takes into account the endogeneity issue. The productivity-export equations allow for an interaction between productivity and exporting, which can help determine the relationship direction, i.e. self-selection versus learning-by-exporting.

[9] Here, productivity and export are endogenous variables and the other variables are exogenous in this step.

4. Data

Our main data for the analysis comes from Sweden's Community Innovation Survey (CIS). The CIS is a pan-European cross-sectional survey that consists of microlevel national data on various aspects of firms' innovation-related activities. This self-reported survey is conducted by the participating countries and the highly consistent questions and methodology among the countries are advantageous for cross-country comparisons. The survey is currently repeated every two years. For an overview of a growing group of empirical studies employing CIS-data see Hall and Mairesse (2006).

For this study, the dataset contains two waves[10]: CIS4 survey that covers the years 2002-2004 and CIS2006 survey that covers the years 2004-2006. The surveys are conducted by Statistics Sweden, with the response rate close to 70 percent and cover both manufacturing and business service sectors.

The advantage of combining the two waves of CIS surveys is the ability to capture a causal relationship between variables of interest and remove the simultaneity bias. So, in this case, the past values of innovation input are able to explain innovation output at the current period, instead of proxying it with the current values. The disadvantage is that the resulting dataset excludes firms that only participate in one of the two waves and thus reduces the observations for the analysis by about 5%. The total number of firms that participate in CIS4 is 1,802 and 1,764 for CIS2006, whereas there are 1,718 firms used in this study.

We complement the CIS data by including the annual firm's registry, ownership structure and export dataset by matching the encoded unique firm identification number. Therefore, we are able to construct a panel dataset for firms that appear in both CIS waves to have a range from 2002-2009. Employing the official registry data is preferable to relying on the self-reported data from the survey, which can suffer from a "questionable quality" (Lööf & Heshmati, 2006).

The description and descriptive statistics of all variables in this paper are presented in Tables 1 and 2 below. We restrict our analysis to the manufacturing sector to focus on firms that export what they actually produce. This is because many exporting firms within the services sector are intermediate trading firms that distribute the products from other domestic firms. So the cost structure is very different from that of manufacturing firms. The sample includes 1,718 firms in total.

Table 7 in the Appendix cross-tabulates all firms according to their innovation and exporting status in the same year. Table 8 shows the *ex post* exporting status several years after the surveys. As we can see, exporters are associated with being innovative, and vice versa. Comparing the two tables, we also see that more innovative firms

[10] Although it is ideal to include three waves to test the recursive relationships from productivity and exporting back to innovation input, the attempt to merge the three waves do not yield a dataset with adequate observations. The variation in many of the variables is rather small that most of the estimates do not have significant results.

become exporters in later years, e.g. 700 and 650 in 2004 and 2006 to 727 and 678 in 2008-2009. This shows that if we allow some lags for innovation, the effect on exporting would be more pronounced.

Table 9 in the Appendix lists the correlation of all variables and the generally low correlation among variables seems to pose no multicollinearity problem for the analysis.

[Tables 1 & 2 about here]

5. Results and discussion

As we elaborate in section 3, the structural model is estimated in three steps: (1) the innovation input equation (Heckman), (2) the innovation production function (OLS), and (3) the productivity & export performance equations (3SLS). We present the results of steps 1 to 3 in Tables 3 to 5, respectively.

In Table 3, the joint estimation of innovation input equations, i.e. equations (1) and (2), is reported. Column (1) is the selection equation corresponding to equation (1). The dependent variable is innovation input propensity, measured as a dummy with value one if total investment in innovation activities are positive from 2002 to 2004 (denoted by *2004*) and from 2004 to 2006 (denoted by *2006*). Column (2) is the outcome equation corresponding to equation (2). The dependent variable is innovation input intensity, measured as logged total investment in innovation activities per employee, observed at the same time as innovation input propensity.

[Table 3 about here]

Table 3 shows that both physical capital and human capital have a positive and significant influence on both the decision and the intensity of innovation input. Firms with more resources are more likely to invest in innovation activities. This is in line with previous studies using CIS data (Crépon et al., 1998; Lööf & Heshmati, 2006). Ownership structure variables are significant only for domestic MNEs, meaning that there is a significant difference if a firm belongs to Swedish MNEs or not when it comes to innovation decisions, while it makes no difference for firms belonging to a uninational corporate group and foreign MNEs. The decision to invest seems more important for Swedish MNEs in order to compete in international markets. On the contrary, this decision is not as important for a uninational corporation that only serves the domestic market or for foreign MNEs because such investments are more likely to be conducted close to the headquarters and less likely at the subsidiaries abroad.

The next table reports the estimation of innovation production function, equation (3), for innovative firms using OLS. The dependent variable is innovation output, measured as logged innovative sales per employee from 2004 to 2006 (denoted by

2006). The main independent variable is lagged innovation input from 2002 to 2004 (denoted by *2004*), which is predicted from the previous step (from Table 3).

[Table 4 about here]

Table 4 shows that past innovation input has a positive (but weakly) significant effect on innovation output, as expected. Firm size and capitals also have positive and significant effects on innovation output of innovative firms. Two of the ownership structure variables, domestic and foreign MNEs, are significant and positive. The results for the ownership variables resonate those in the first step, where it is more important for Swedish MNEs than for uninational corporation or foreign MNEs.

The last step of the estimation is reported in Table 5. Here, we estimate equations (4) and (10) simultaneously. The chosen estimator is 3SLS.

The predicted lagged innovation output in 2006 is used as the main explanatory variable for productivity. This variable is obtained from the second step (Table 4). The dependent variables are productivity and export performance measured as total export value during 2008-2009, columns (4) and (5).

From the results of productivity equation in Table 5, innovation output is positive and significant, which means that we can reject the null hypothesis 2 (*HP2*). A doubling increase in innovation output is associated with 16.1% increase in firm's productivity. The finding is in line with other similar studies. Our estimate size 0.161 is slightly higher than 0.121 in Lööf & Heshmati (2006). In Crépon et al. (1998), the Asymptotic Least Squares estimate in the second step is 0.308, or roughly twice compared to our result. In Antonietti & Cainelli (2011), their measure of innovation output is a binary variable, but they also find a positive and significant effect of innovation output on firms' total factor productivity.

The positive and highly significant result for productivity suggests that it can explain the export performance, which is in line with the self-selection literature (Melitz, 2003, among others). This means that we are able to reject the null hypothesis 1 (*HP1*). It also implies that we find significant evidence that the export intensity is driven by firms' productivity level. In terms of the magnitude, a doubling increase in firms' productivity level leads to an increase in export value by approximately twice. Although other studies have used different measures of exports, e.g. share of export per total sales or the number of destination regions, they also find this positive effect of productivity of firms' exports (Antonietti & Cainelli, 2011; Wagner, 2008).

On the other hand, exports are not significant in explaining productivity, which means this paper does not find evidence to support the learning-by-exporting argument. For past export experience, it is positive and highly significant in explaining current export performance, confirming the persistency of exporting. Furthermore, physical capital and human capital are also positive and significant in explaining productivity, as we expect. Ownership structure variables, i.e. domestic and foreign MNEs, are positive and significant only for the export performance.

In summary, the structural framework adopted in this paper reveals the mechanics behind the export behavior of firms. Productive firms become exporters and there is no evidence that exporting leads a firm to be productive. The source of such productivity heterogeneity is the innovative performance (output) of firms in the past. Lastly, such innovative output is the result of the amount of investment in innovation activities and the decision to invest in the past.

As an alternative approach, we allow for an interaction between innovation output, productivity, and exporting in a simultaneous setting. Table 6 in the Appendix lists the results. We first estimate the three equations, equations (3), (4), and (10), separately by OLS, then simultaneously by 3SLS. The Hausman test rejects the null hypothesis of simultaneity. Once again, the results suggest that lagged innovation input has an impact on current innovation output, and productivity has an impact on the export intensity. This means using an alternative estimation strategy does not change our main results.

The export intensity is positive and significant in explaining both innovation output and productivity. However, the positive impact on productivity is not in line with the results based on three-step procedure estimation strategy. One possible reason may be due to the difference in timing between the two methodologies, i.e. the two-step approach treats both exports and productivity in the same year, whereas the three-step approach has a lag of two years. We prefer to rely more on the three-step procedure estimation strategy since it allow us to use the lag between in our structural equations. Moreover, the mixed results seem to be common in empirical studies dealing with the productivity-export association (for example, in a cross-country study by ISGEP , 2008).

[Table 5 about here]

6. Conclusion

It is well known that exporters are productive firms. But the source of their productivity is left unexplained. This paper aims to endogenize the productivity heterogeneity of exporting firms by incorporating innovation in a structural model framework. In doing so, we close the gap between the innovation-productivity and productivity-export literature.

There are two novelties in this paper. Firstly, we open the black box concerning the source of productivity heterogeneity of exporting firms. Although we know that productive firms can start exporting later, we answer to the question why those firms are productive in the first place. Secondly, by merging the two waves of Swedish CIS data and tracing the participants' behavior from 2002 to 2009, it becomes possible to (i) consider lagged value of innovation input to explain future innovation output, and then (ii) consider the innovation output to explain further future productivity and export performance. It implies that we (i) allow a lead time for innovation input to impact on innovation output and also (ii) leave time for innovation output to have its effect on productivity and export performance. Such a structure can substantially reduce the reverse causality and endogeneity bias.

The main findings are that exporters are productive firms that cross the productivity threshold. They have passed it because they succeed in appropriating the innovation output in the past, which is driven in turn by the decision and amount of investment in various investments in innovation activities.

The implication of the findings is that export promotion policies could be more effective if they target firms that have succeeded in their innovation activities. This is because these innovative firms are more likely to improve their productivity and will be more likely to afford the entry costs of exporting later. Note that the amount of firms' innovation investments alone may not necessarily lead to a desirable objective, but the output as a result of a successful investment does.

Table 1: Variable description

VARIABLES	Description	Source	Expected Sign
Firm Size	Total number of employees at current year.	Firm's registry database	+
Physical Capital	Total costs of building, land, and machinery, in current SEK.	Firm's registry database	+
Human Capital	The share of highly-educated employees with at least three years of tertiary education per total employees.	Firm's registry database	+
Uninational	A dummy taking a value of 1 if the firm belongs to a domestic corporation group, 0 otherwise.	Firm's ownership structure database	+/-
Domestic MNEs	A dummy taking a value of 1 if the firm is affiliated with Swedish multinational enterprises, 0 otherwise.	Firm's ownership structure database	+/-
Foreign MNEs	A dummy taking a value of 1 if the firm is affiliated with multinational enterprises with headquarter(s) outside of Sweden, 0 otherwise	Firm's ownership structure database	+/-
Cooperation	A dummy taking a value of 1 if the firm has a formal external cooperation agreement, 0 otherwise.	CIS	+
Innovation Input Propensity	A dummy taking a value of 1 if the firm has positive investments in innovation input.	Author-generated using CIS data	
Innovation Input	Total investments in at least one of the six categories in innovation-related activities, according to the Oslo manual, in SEK.	CIS	+
Innovation Output	Total sales for innovative products, in SEK.	CIS	+
Productivity	Value-added per employee, in SEK.	Firm's registry database	+
Export Intensity	Total export value, in SEK.	Firm's export database	+
Export Experience	A dummy taking a value of 1 if the firm has had exporting experience during 1997-2002, 0 otherwise.	Author-generated using firm's export database	+

Table 2: Descriptive statistics

VARIABLES	Obs.	Mean	Std. Dev.	Minimum	Maximum
Firm Size	13,297	217.701	1161.340	1	39,554
Physical Capital	13,051	966,258	14,189,676	52.652	1,531,052,672
Human Capital	13,318	0.137	0.182	0	1
Uninational	13,744	0.317*		0	1
Domestic MNEs	13,744	0.217*		0	1
Foreign MNEs	13,744	0.221*		0	1
Cooperation	1,917	0.497*		0	1
Innovation Input Propensity	13,744	0.127*		0	1
Innovation Input	3,410	43,973	475,486	0	22,580,646
Innovation Output	1,707	726,850	22,300,500	0	921,102,016
Productivity	13,016	760,477	2,864,570	2,547	278,207,168
Export Intensity	6,615	828,166	1,951,721	0.008	38,253,308
Export Experience	7,895	0.788*	0.409	0	1

* The fraction of observations with value 1.

Table 3: Step 1 - Innovation Input determinants

Dependent variable: Innovation Input *(logged Total innovation investment per employee)*
Estimation: Generalized Tobit model (Heckman using FIML)

VARIABLES	(1) **Selection Equation** **Innovation Input** $_{2004,\ 2006}$ **(Propensity)**	(2) **Outcome Equation** **Innovation Input** $_{2004,\ 2006}$ **(Intensity)**
Firm Size *(log) (2004, 2006)*	**0.235***** (0.030)	
Physical Capital *(log) (2004, 2006)*	**0.122***** (0.024)	**0.330***** (0.040)
Human Capital *(log) (2004, 2006)*	**1.288***** (0.314)	**3.755***** (0.431)
Uninational	0.114 (0.079)	0.180 (0.141)
Domestic MNEs	**0.277***** (0.097)	**0.219*** (0.133)
Foreign MNEs	0.077 (0.099)	0.181 (0.137)
Constant	-3.416*** (0.531)	-2.749* (1.513)
Observations	2,135	-
Uncensored Obs.	-	1,244
Industry dummies	YES	YES
Year dummies	YES	YES

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
LR test of independency: $\chi^2(1) = 35.77$ with p = 0.000

Table 4: Step 2 - Innovation Input to Innovation Output

Dependent variable: Innovation Output *(logged Innovative Sales per employee)*
Estimation: OLS with the predicted value of Innovation Input from step 1

VARIABLES	(3) **Innovation Output** *2006*
Innovation Input *(Predicted) (lagged: 2004)*	**0.333*** (0.187)
Firm Size *(log)(lagged: 2004)*	**0.370***** (0.112)
Physical Capital *(log)(lagged: 2004)*	**0.347***** (0.104)
Human Capital *(log)(lagged: 2004)*	**3.068***** (0.914)
Cooperation *(lagged: 2004)*	0.038 (0.152)
Uninational	0.199 (0.249)
Domestic MNEs	**0.730***** (0.278)
Foreign MNEs	**0.463*** (0.238)
Inverted Mills ratio *(2006)*	**5.071***** (1.466)
Constant	0.333* (0.187)
Observations (innovative firms)	378
R-squared	0.131
Industry dummies	YES

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Step 3 - Innovation Output to Productivity & Export

Dependent variables: Productivity: *(logged Value Added per employee),* Export: *(logged Export value per employee)*
Estimation: Three-stage Least Square (3SLS)

VARIABLES	(4) Productivity *(2008-2009)*	(5) Export Intensity *(2008-2009)*
Innovation Output *(Predicted)(log) (2006)*	**0.161****	
	(0.074)	
Productivity *(log) (2008-2009)*		**2.017*****
		(0.770)
Export Intensity *(log) (2008-2009)*	-0.027	
	(0.080)	
Export Experience *(2006)*		**2.867****
		(1.135)
Size *(log) (2008-2009)*	0.017	0.025
	(0.032)	(0.099)
Physical Capital *(log) (2008-2009)*	**0.084*****	
	(0.031)	
Human Capital *(log) (2008-2009)*	**0.614***	
	(0.348)	
Uninational	0.085	0.070
	(0.083)	(0.484)
Domestic MNEs	0.135	1.400***
	(0.155)	(0.492)
Foreign MNEs	0.169	1.532***
	(0.174)	(0.554)
Constant	10.510***	-17.994*
	(0.913)	(9.485)
Observations	435	435
R-squared	0.102	0.174
Industry dummies	YES	YES

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table 6: Step 2 - Innovation Output, Productivity, and Export Performance

Dependent variables: *logged Innovative sales per employee), logged Value added per employee),* and *logged Total Export value per Employee*
Estimation: Equation-by-equation OLS, Simultaneous equations (3SLS) with bootstrapped standard errors.

VARIABLES	(6)	(7)	(8)	(9)	(10)	(11)
		OLS (2006)			3SLS (2006)	
	Innovation Output	Productivity	Export Intensity	Innovation Output	Productivity	Export Intensity
Innovation Input *(Predicted) (lagged: 2004)*	0.292** (0.129)			0.288* (0.151)		
Innovation Output *(log) (2006)*		0.011 (0.056)			0.007 (0.062)	
Productivity *(log) (2006)*			4.388*** (0.813)			4.414*** (0.764)
Export Intensity *(log) (2006)*	0.197* (0.104)	0.122*** (0.023)		0.199* (0.112)	0.123*** (0.029)	
Export Experience *(2006)*			2.393 (2.574)			2.370 (2.496)
Process Innovation *(2006)*		0.005 (0.036)			0.004 (0.042)	
Size *(log) (2006)*	0.016 (0.057)	0.012 (0.016)	-0.175*** (0.063)	0.015 (0.062)	0.012 (0.012)	-0.176*** (0.066)
Physical Capital *(log) (2006)*	0.021 (0.074)	0.059*** (0.020)		0.019 (0.067)	0.059*** (0.018)	
Human Capital *(2006)*	1.335* (0.744)	0.617*** (0.214)		1.318* (0.758)	0.620** (0.261)	
Cooperation *(2006)*	0.098 (0.114)			0.096 (0.142)		
Uninational	-0.207 (0.204)	-0.005 (0.079)	0.036 (0.472)	-0.209 (0.255)	-0.006 (0.078)	0.035 (0.401)
Domestic MNEs	-0.269 (0.238)	-0.027 (0.080)	1.110*** (0.418)	-0.277 (0.296)	-0.029 (0.105)	1.105** (0.430)
Foreign MNEs	-0.393 (0.262)	-0.053 (0.082)	1.230*** (0.406)	-0.399 (0.285)	-0.056 (0.103)	1.225*** (0.438)
Inverted Mills ratio *(2006)*	1.360* (0.777)			1.322 (0.873)		
Constant	7.161*** (1.694)	10.890*** (0.730)	-48.264*** (11.116)	7.210*** (2.152)	10.924*** (0.775)	-48.584*** (10.292)
Observations	328	328	328	328	328	328
R-squared	0.131	0.328	0.406	0.131	0.328	0.406
Industry dummies	NO	NO	NO	NO	NO	NO

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
**Note*: Hausman test of OLS vs. 3SLS reject the null hypothesis of simultaneity.

Table 7: Export and innovation status of firms by year

	Exporter (2004 & 2006)		Nonexporters (2004 & 2006)		Total (2004 & 2006)	
	Firms	%*	Firms	%*	Firms	%*
Innovators (2004)	700	40.75	200	11.64	900	52.39
Noninnovators (2004)	427	24.85	391	22.76	818	47.61
Innovators (2006)	650	37.83	189	11.00	839	48.84
Noninnovators (2006)	476	27.71	403	23.46	879	51.16

* Percentage of total number of firms = 1,718. The year of the export status corresponds to the innovation status, e.g. 700 firms are innovators in 2004 and are also exporters in 2004.

Table 8: Export status of firm in later years

	Exporter (2008-2009)		Nonexporters (2008-2009)		Total (2008-2009)	
	Firms	%*	Firms	%*	Firms	%*
Innovators (2004)	727	42.32	173	10.07	900	52.39
Noninnovators (2004)	350	20.37	468	27.24	818	47.61
Innovators (2006)	678	39.46	161	9.37	839	48.84
Noninnovators (2006)	517	30.09	362	21.07	879	51.16

* Percentage of total number of firms = 1,718. The year of the innovation status is 2004 and 2006, whereas the year of the export status is 2008 and 2009.

Table 9: Correlation table

	Firm Size	Physical Capital	Human Capital	Uni national	Domestic MNEs	Foreign MNEs	Coope-ration	Inno. Input Propensi ty	Inno. Input	Inno. Output	Produc-tivity	Export Intensity	Export Experience
Firm Size	1.000												
Physical Capital	0.240***	1.000											
Human Capital	0.085**	-0.177***	1.000										
Uninational	-0.283***	-0.017	-0.092**	1.000									
Domestic MNEs	0.179***	-0.014	0.080**	-0.367***	1.000								
Foreign MNEs	0.324***	0.074*	0.039	-0.356***	-0.483***	1.000							
Cooperation	0.267***	0.124***	0.188***	-0.113***	0.119***	0.016	1.000						
Inno. Input Propensity	0.086**	0.110***	0.028	0.018	0.047	-0.045	0.151***	1.000					
Innovation Input	-0.001	0.083**	0.113***	-0.056	0.047	-0.032	0.185***	0.444***	1.000				
Innovation Output	0.052	0.042	0.129***	-0.126***	0.015	0.101**	0.124***	0.014	0.195***	1.000			
Productivity	0.254***	0.282***	0.249***	-0.127***	0.050	0.186***	0.188***	0.003	0.011	0.219***	1.000		
Export Intensity	0.110***	0.184***	-0.106***	-0.213***	0.211***	0.084**	0.126***	0.101**	0.073*	0.143***	0.168***	1.000	
Export Experience	0.143***	0.014	-0.040	-0.155***	0.124***	0.067*	0.087**	0.008	0.053	0.083**	0.076*	0.321***	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

References

Aghion, P., & Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica, 60*(2), 323-351. doi: 10.2307/2951599

Aghion, P. A., Howitt, P. A., Brant-Collett, M., & Peñalosa, C. G. (1998). *Endogenous Growth Theory*: MIT Press.

Andersson, M., & Lööf, H. (2009). Learning-by-Exporting Revisited: The Role of Intensity and Persistence*. *Scandinavian Journal of Economics, 111*(4), 893-916. doi: 10.1111/j.1467-9442.2009.01585.x

Antonietti, R., & Cainelli, G. (2011). The role of spatial agglomeration in a structural model of innovation, productivity and export. *Annals of Regional Science, 46*, 577-600.

Aw, B. Y., Roberts, M. J., & Winston, T. (2007). Export market participation, investments in R&D and worker training, and the evolution of firm productivity. *The World Economy, 30*(1), 83-104.

Aw, B. Y., Roberts, M. J., & Xu, D. Y. (2008). R&D investments, exporting, and the evolution of firm productivity. *The American Economic Review*, 451-456.

Aw, B. Y., Roberts, M. J., & Xu, D. Y. (2011). R&D Investment, Exporting, and Productivity Dynamics. *American Economic Review, 101*(4), 1312-1344. doi: doi: 10.1257/aer.101.4.1312

Bernard, A. B., Eaton, J., Jensen, J. B., & Kortum, S. (2003). Plants and Productivity in International Trade. *The American Economic Review, 93*(4).

Bernard, A. B., & Jensen, J. B. (1999). Exceptional exporter performance: cause, effect, or both? *Journal of International Economics, 47*(1), 1-25.

Bernard, A. B., & Wagner, J. (1997). Exports and Success in German Manufacturing. *Review of World Economics, 133*(1), 134-157.

Brouwer, E., & Kleinknecht, A. (1997). Measuring the unmeasurable: a country's non-R&D expenditure on product and service innovation. *Research Policy, 25*(8), 1235-1242.

Cantwell, J. (1989). Technological innovation and multinational corporations.

Castellani, D., & Giovannetti, G. (2010). Productivity and the international firm: dissecting heterogeneity. *Journal of Economic Policy Reform, 13*(1), 25-42. doi: 10.1080/17487870903546226

Castellani, D., & Zanfei, A. (2007). Internationalisation, Innovation and Productivity: How Do Firms Differ in Italy? *World Economy, 30*(1), 156-176. doi: 10.1111/j.1467-9701.2007.00875.x

Clerides, S. K., Lach, S., & Tybout, J. R. (1998). Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco. *The Quarterly Journal of Economics, 113*(3), 903-947. doi: 10.1162/003355398555784

Cohen, W. M. (Ed.). (1995). *Empirical Studies of Innovative Activity*. Oxford: Blackwell.

Crépon, B., Duguet, E., & Mairesse, J. (1998). Research investment, innovation and productivity: An econometric analysis. *Economics of Innovation and New Technology, 7*(2), 115-158.

Delgado, M. A., Fariñas, J. C., & Ruano, S. (2002). Firm Productivity and Export Markets: A Non-Parametric Approach. *Journal of International Economics, 57*(2), 397-422.

Doraszelski, U., & Jaumandreu, J. (2013). R&D and productivity: Estimating endogenous productivity. *The Review of Economic Studies, 80*(4), 1338-1383.

Eaton, J., Kortum, S., & Kramarz, F. (2004). Dissecting trade firms, industries, and export destinations *Federal Reserve Bank of Minneapolis, Research Department staff report 332* Retrieved from http://woodrow.mpls.frb.fed.us/research/sr/sr332.html

Ederington, J., & McCalman, P. (2008). Endogenous firm heterogeneity and the dynamics of trade liberalization. *Journal of International Economics, 74*(2), 422-440. doi: http://dx.doi.org/10.1016/j.jinteco.2007.07.001

Greene, W. H. (2003). *Econometric analysis*: Prentice Hall.

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

Griliches, Z. (2000). *R&D, Education, and Productivity: A Retrospective*. Cambridge, Mass.: Harvard Univ. Press.

Hall, B. H., & Mairesse, J. (2006). Empirical studies of innovation in the knowledge-driven economy. *Economics of Innovation and New Technology, 15*(4/5), 289-299.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica, 47*(1), 153-161.

Howitt, P. (2000). Endogenous Growth and Cross-Country Income Differences. *The American Economic Review, 90*(4), 829-846.

ISGEP. (2008). Understanding Cross-Country Differences in Exporter Premia: Comparable Evidence for 14 Countries. *Review of World Economics, 144*(4), 596-635. doi: 10.1007/s10290-008-0163-y

Kleinknecht, A., Van Montfort, K., & Brouwer, E. (2002). The non-trivial choice between innovation indicators. *Economics of Innovation and New Technology, 11*(2), 109-121.

Klette, T. J., & Kortum, S. (2004). Innovating Firms and Aggregate Innovation. *Journal of Political Economy, 112*(5), 986-1018.

Long, N. V., Raff, H., & Stähler, F. (2011). Innovation and Trade with Heterogeneous Firms. *Journal of International Economics, 84*(2), 149-159.

Lööf, H., & Heshmati, A. (2006). On the relationship between innovation and performance: A sensitivity analysis. *Economics of Innovation and New Technology, 15*(4/5), 317-344.

Maican, F., Orth, M., Roberts, M. J., & Vuong, V. A. (2013). *R&D Dynamics and its Impact on Productivity and Export Demand in Swedish Manufacturing*.

Mairesse, J., & Mohnen, P. (Eds.). (2010). *Using innovation surveys for econometric analysis* (Vol. 2). London: Burlington Academic Press.

Mairesse, J., & Robin, S. (Eds.). (2012). *The importance of Process and Product Innovation for Productivity in French Manufacturing and Service Industries*. Oxford: Oxford University Press.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica, 71*(6), 1695-1725.

Mohnen, P., Mairesse, J., & Dagenais, M. (2006). Innovativity; A comparison across seven European countries. *Economics of Innovation and New Technology, 15*(4/5), 391-413.

OECD. (2005). Oslo Manual: guidelines for collecting and interpreting innovation data. Paris: OECD and Eurostat.

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica, 64*(6), 1263-1297.

Pakes, A., & Griliches, Z. (1984). Patents and R&D at the firm level: A first look. In Z. Griliches (Ed.), *R&D, Patents, and Productivity* (pp. 55-72). Chicago: University of Chicago Press.

Peters, B., Roberts, M. J., Vuong, V. A., & Fryges, H. (2013). Estimating dynamic R&D demand: An analysis of costs and long-run benefits: National Bureau of Economic Research.

Roberts, M. J., & Tybout, J. R. (1997). The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs. *The American Economic Review, 87*(4), 545-564.

Romer, P. (1990). Endogenous Technological Change. *Journal of Political Economy, 98*, 71-102.

Schmitz Jr, J. A. (2005). What determines productivity? Lessons from the dramatic recovery of the US and Canadian iron ore industries following their early 1980s crisis. *Journal of Political Economy, 113*(3), 582-625.

Schumpeter, J. A. (1934). *The theory of economic development: an inquiry into profits, capital, credit, interest, and the business cycle*: Transaction Books.

Segerstrom, P., & Stepanok, I. (2011). Learning How to Export *Working Paper Series in Economics and Finance*: Stockholm School of Economics.

Wagner, J. (2007). Exports and Productivity: A Survey of the Evidence from Firm-level Data. *World Economy, 30*(1), 60-82. doi: 10.1111/j.1467-9701.2007.00872.x

Verbeek, M. (2008). *A guide to modern econometrics* (3 ed.). West Sussex: John Wiley & Sons.