The impact of offshoring on productivity and innovation: Evidence from Swedish manufacturing firms*

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Abstract

This paper examines the impact of offshoring on total factor productivity (TFP) and innovation measured by patent applications. It applies instrumental variable and matching approaches on a panel of about 7,500 Swedish manufacturing firms over the period 2001–2014, and identifies offshoring-related intermediate imports by the United Nations Broad Economic Categories system. Accounting for selection and simultaneity bias, no causal impact on TFP can be established, while the estimated positive effect on innovation is found to be weakly significant.

Keywords: offshoring, patents, total factor productivity, self-selection, reverse causality
JEL classification: C33, F61, D24, L23, O31

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1 Introduction

With the advent of offshoring in the 1990s, a new phase of the contracting-out phenomenon was introduced. Explanations for this development can be sought among a handful of key factors: technological advances, institutional developments favoring trade liberalization, competitive pressures to reduce costs, and the potential for improved productivity (Olsen 2006). The single most important factor is the digitization of the economy, which has opened the potential for conducting business activities in entirely new ways, and in an extended spatial area in which a supply chain of local, regional and international firms produces various inputs.

International trade theory is ambiguous about the importance of offshoring. While some of the literature predicts that offshoring of business functions to locations outside of the firm's national borders stimulates innovation and productivity, other authors explore why offshoring may have only a negligible impact on renewal and growth in the focal firm, at least above some threshold level. While offshoring may improve firms' innovation capabilities by replacing labor-intensive and routine tasks with cognitive and non-routine ones, offshoring production of intermediates may also reduce the feedback from production to process research efforts.

Existing empirical research has not provided clear support for either one of these opposing theoretical predictions. Possible explanations for the lack of consensus in empirical research relate to the difficulties in observing the extent both of offshoring and firm performance, as well as methodological challenges to sort out causality, as innovative and highly productive firms are likely to buy more imported inputs (Hummels, Jørgensen, Munch & Xiang 2014).

The purpose of this paper is to address some shortcomings in previous studies on the impact of offshoring on innovation and productivity. To do so we (i) study the universe of manufacturing companies (with at least 10 employees) in an industrialized economy, (ii) follow these companies with an unbalanced panel consisting of unique employer-employee data for a 14-year period, (iii) observe detailed company and employee characteristics, (iv) deal with both selection and simultaneity issues, (v) increase the precision of our estimates by controlling for both routine tasks at the individual level (Frey–Osborne Index) and offshorable activities (Blinder Index), and (vi) take advantage of the United Nations Broad Economic Categories (BEC) to distinguish offshoring-related imports from other imported goods. Using a panel of about 7,500 Swedish manufacturing firms over the period 2001–2014, our random effects probit models and fixed effects instrumental variable models suggest that offshoring may be positively associated with both patent applications and total factor productivity. We then estimate an empirical model with offshoring firms defined by a threshold where the input received through offshoring corresponds to at least to 10% of the firms' sales, and a control group consisting of otherwise similar companies. The results suggest that the link between offshoring and technical change may be largely explained by self-selection and reverse causality. Accounting for these factors, we find no causal impact on TFP and a causal positive impact of offshoring on innovation measured by patents, albeit at a low level of statistical significance.

The rest of the paper is structured as follows. Section 2 surveys the related literature. Section 3 presents the data and the outcome variables. Section 4 details the empirical strategy, Section 5 reports the results, and Section 6 concludes.

2 Related literature

In the three last decades, a key feature of the global economy is the growth of offshoring in production and service tasks that were previously produced domestically (Feenstra & Hanson 2003, Hummels, Jørgensen, Munch & Xiang 2014). Intermediate inputs now account for two-thirds of world trade (Acemoglu, Gancia & Zilibotti 2015).

The question how increased input from foreign sources affects firms' innovation and technological change has been studied primarily in the theoretical literature, and to a lesser extent in different strands of the empirical literature. A major focus of this research are the indirect effects through changes in the composition of the labor force: the ratio between skilled and unskilled workers and their relative wages. Offshoring generally involves unbundling and relocating labor-intensive work tasks from the focal firm to foreign firms with lower labor costs, while cognitive and non-routine activities that require specialized skills and technologies remain in house (Baldwin 2016, Yamashita & Yamauchi 2019). However, Blinder (2009) and Blinder & Krueger (2013) argue that low-skilled and high-skilled jobs are equally likely to be affected by offshoring. Instead of low skill-intensity, the main candidates for offshorability are jobs lacking requirements of physical contact and geographic proximity (Blinder 2006), as well as jobs associated with codifiable instructions (Leamer & Storper 2001) and automation (Frey & Osborne 2017).

Economic research on offshoring has theoretical roots in several different disciplines. They include, among others, the proposition that firms can increase their productivity by focusing on what they do best and outsource the rest (Coase 1937), the related comparison of the global value-chain process with the Ricardian principle of comparative advantage (Porter 1985), the concept of an international product cycle proposed by Vernon (1966), the endogenous theories on trade, spillovers and growth by Grossman & Helpman (1991), as well as the literature on shifting production from North (West) to South (East) aimed at raising rate of innovation and productivity in the North (West) (Branstetter & Saggi 2011, Chung & Yeaple 2008, Naghavi & Ottaviano 2009). Also of note are discussions of trade-induced technical change (Bloom, Draca & Van Reenen 2016), the skill-biased technical change literature on offshoring (Acemoglu, Gancia & Zilibotti 2015), concepts of offshoring driven by fractionalization of production that unbundles supply chains into finer stages across countries (Grossman & Rossi-Hansberg 2008), and theories on the weakened feedback from offshoring sources to R&D investing firms due to imperfect knowledge spillovers (Naghavi & Ottaviano 2009).

Broadly, the theoretical literature on offshoring predicts two possible outcomes for firms' innovation and productivity when they relocate production overseas. On the one hand, offshoring can improve firm performance through within-firm resource allocation and efficiency gains. The second is that it can slow the rate of innovation and productivity by limiting the possibility of knowledge creation and transfers between R&D operations and production due to physical separation. Empirical assessment of these conflicting hypotheses has not reached a consensus on the net effect of offshoring. Below, we summarize some of the divergent results in recent literature.

Yamashita & Yamauchi (2019) study Japanese multinational firms for the period 1995–2011 and find that increased offshore production has little effects on onshore innovation performance as measured with patent statistics. Moreover, the authors report weak evidence that increased offshore production degrades the quality of innovation, as measured by patent citations. This finding is consistent with the theoretical predictions of the negative effect of the separation of production to offshore locations and domestic innovation activities. Similar results are reported by Branstetter, Chen, Glennon, Yang & Zolas (2017). They study the Taiwanese electronics industry where exogenous policy changes led to a significant decrease in the offshoring costs for Taiwanese firms. This fact was exploited to identify the causal relationship between offshoring and innovation, as measured by patenting. The authors find that firms' propensity of innovation was reduced as a causal effect of greater offshoring of production to China.

In contrast to the main finding in these studies, Bøler, Moxnes & Ulltveit-Moe (2015) show that imported intermediate goods stimulate R&D among Norwegian firms. Other studies reporting a positive causal impact of offshoring on firms' innovation include Dachs, Ebersberger, Kinkel & Som (2015) who study data for more than 3000 manufacturing firms from seven European countries. They present evidence that offshoring firms employ a higher share of R&D and design personnel, introduce new products more frequently to the market, and invest more frequently in advanced process technologies compared to non-offshoring firms. A positive net effect of offshoring is also reported by Fritsch & Görg (2015). They use firm-level data for over 20 emerging market economies to investigate the link between outsourcing and innovation. Their study shows that outsourcing is associated with a greater propensity invest in research and development, to introduce new products, and to upgrade existing products.

Most closely related to the empirical observations in our study, Tingvall & Karpaty (2011) use data on Swedish multinational firms and find that offshoring to other European countries and North America has a negative effect on R&D intensity at home. However, offshoring to emerging economies is found to have a negligible or even a positive effect on R&D intensity. The latter finding is in line with the theoretical argument on offshoring as a strategy to specialize in knowledge-intensive activities while more routine-based production processes are offshored to exploit lower labor costs. However, the results are not consistent with the assumptions that offshoring to technologically advanced countries may provide access to higher quality inputs, allowing firms to absorb knowledge spillovers on new technologies (Abramovsky & Griffith 2006).

The empirical literature also provides support for the hypothesis of inverted U-shape impact of offshoring. Based on a panel dataset of R&D-active firms in Germany, Steinberg, Procher & Urbig (2017) distinguish between R&D offshoring to foreign affiliates and external foreign parties and find that both offshoring strategies, when pursued intensively, eventually harm firms' innovation performance. Other studies that confirm the existence of an inverted U-shape pattern of offshoring on innovation include Hurtado-Torres, Aragón-Correa & Ortiz-de Mandojana (2017). Their paper considers how geographical diversification of firms' R&D offshoring affects innovation performance among multinational enterprises (MNEs) in the energy industry.

In contrast to the still limited firm-level studies on internal innovation and productivity effects of offshore production, the literature has devoted substantial attention to the overall impact of offshoring. This research considers consequences on the spatial, industrial or national level in the offshoring economy. While the significance of international fragmentation of production is unclear at company level, there is a more coherent and positive picture at the aggregate level. For instance, Bloom, Draca & Van Reenen (2016) examine the impact of Chinese import competition on several measures of technical change—patenting, IT, and TFP—using panel data across twelve European countries from 1996–2007. They suggest that the absolute volume of innovation increases within the firms most affected by Chinese imports in their output markets. Castellani & Pieri (2013) show that productivity growth of 262 regions in Europe is associated with offshoring of R&D activities by domestic multinational enterprises based these regions. They find a large positive correlation between the extent of R&D offshoring and the home region's productivity growth.

In summary, the empirical literature suggests that no definite conclusions can be drawn about positive or negative causal effects of offshoring on innovation and productivity. Many studies propose that the disadvantages outweigh the advantages, and among studies with positive results there are indications that offshoring is only an effective strategy up to a certain threshold level.

One explanation for the heterogeneous results in existing studies of the relationship between offshoring, innovation and technological development is that they capture actual differences in outcomes between products, companies, industries, and destinations, as well as the importance of the scope of the outsourced activities.

It may also be the case that the results across studies are not comparable due to differences in the quality of data, measurement of offshoring, and measurement of innovation and productivity. Another key issue is how the studies have been able to correct for endogeneity. There is extensive evidence in the literature that more innovative firms are those that aggressively engage in offshoring in production (Yamashita & Yamauchi 2019). The decisions of engaging in offshore production and innovation are therefore endogenous to individual firms. Researchers have addressed this challenge with various empirical approaches such as instrumental variables estimation. Recently, a small number of studies have exploited the occurrence of exogenous shocks (Bloom, Draca & Van Reenen 2016, Autor, Dorn, Hanson, Pisano, Shu et al. 2016, Branstetter, Chen, Glennon, Yang & Zolas 2017, Bøler, Moxnes & Ulltveit-Moe 2015). Propensity score matching is another approach that has been used to analyse the causal effect of offshoring on innovation. For instance, Dachs, Ebersberger, Kinkel & Som (2015) use a propensity score matching estimator to identify a control group of non-offshoring firms with characteristics similar to those of offshoring firms.

3 Data

The data in our study come from several sources. The combined employer-employee dataset is obtained from Statistics Sweden, and covers the population of Swedish manufacturing firms (2-digit NACE Rev.2 codes 10–37) and their employees for 2001–2014. Similar to most other studies using Swedish trade data, we only consider firms with 10 or more employees, as the information provided for smaller firms is likely to be less reliable.

The employer dataset contains information on sales, value added, exports, imports, capital stock, corporate ownership structure and number of employees at the firm level. Continuous variables are deflated using deflators for exports, imports and producer prices provided by Statistics Sweden. Firm-level data are matched with patent data retrieved from the European Patent Office (EPO). By merging this data with the employee dataset, we can access information on employees' level of education, occupation and income levels.

Beginning with Feenstra & Hanson (1999), researchers have defined offshoring as imports of intermediate inputs. More recent research has advanced the identification by measuring offshoring as imports of the same four-digit industries (Hummels, Jørgensen, Munch & Xiang 2014), or same six-digit industries that importers produce domestically

(Bernard, Fort, Smeets & Warzynski 2020).

In this paper, we apply a different approach to identify relocated production of inputs. As offshoring production leads to firms' imports, it is possible to take advantage of the United Nations Broad Economic Categories (BEC), which is a three-digit classification system grouping transportable goods according to their main end use: capital goods, consumer goods and intermediate goods. The latter has been applied as a proxy for offshoring. A main challenge for offshoring research based on the BEC system is that revisions imply that unique products might be classified differently over time. To account for the re-classification, we apply the algorithm suggested by Pierce & Schott (2012) and further developed by Van Beveren, Bernard & Vandenbussche (2012) for concording trade and production data over time, and consider an imported product as offshored if it is classified as an intermediate good. The offshoring variable is defined in Table 8.

To mitigate possible bias due to spurious correlation, we control for the potential trends that may make jobs more likely to be offshored[1] using the Blinder index of offshorability.[2] Applying the classification method proposed by Blinder & Krueger (2013), we first consider 430 job titles in the Swedish labor market and estimate their offshorability. Each occupation is then classified according to whether it has a high risk of being moved abroad. We then calculate a firm-specific offshorability measure, defined as the ratio of offshorable jobs to total employment.

We also include the Osborne–Frey index (Frey & Osborne 2017) in our analyses. This index is designed to capture the likelihood for each occupation to be replaced by computers or robots in the near future. The computed Osborne–Frey index is also firm-specific.

Our study evaluates patent applications and TFP as measures of the importance of offshoring. Despite well-known advantages and shortcomings, both are widely used in academic literature as indicators of technological change and economic development. Patents are the only source of rich information on new technology screened in a systematic and resource-intensive manner over a long period of time within and across technology classes.

[1] A wide variety of occupations in both manufacturing and services are vulnerable to offshoring to foreign countries. For instance, Blinder & Krueger (2013) estimate the potential offshorability to be about one-quarter of all jobs in the 2004 US workforce.

[2] Blinder & Krueger (2013) find that jobs that can be broken down into simple routine tasks are easier to offshore in comparison to other more complex, non-routine tasks. The common characteristic of offshorable occupations is the lack of face-to-face contact with end users.

Patent information are accessible through large databases maintained by organizations such as the National Bureau of Economic Research (NBER), the European Patent Office (EPO), and the Institute of Intellectual Property (IIP) in Japan. However, there are certainly caveats. Not all patents represent innovation, nor are all innovations patented; the distribution of the value of patents is highly skewed, and companies may use patents strategically to block other firms' patents by creating a 'patent thicket'. For a review on patents as an indicator of innovation, see for instance Nagaoka, Motohashi & Goto (2010). In the paper, we exploit the world's largest patent data base, the EPO Worldwide Patent Statistical Database (PATSTAT) that covers 172 countries.

TFP has its own measurement problems, such as its procyclicality and the difficulty in obtaining an accurate price index, particularly for goods with rapid quality changes. A main challenge in estimating TFP is that due to positive productivity shocks, firms tend to respond by expanding their level of output and by demanding more inputs, and vice versa for a negative shock. The positive correlation between the observable input levels and the unobservable productivity shocks is a source of bias in TFP. Recent years have seen a number of methodological developments of TFP computation addressing this bias. Olley & Pakes (1996), Levinsohn & Petrin (2003), Ackerberg, Caves & Frazer (2006, 2015), Manjón & Mañez (2016) have contributed to the literature proposing two-step estimation procedures, while Wooldridge (2009) provided a method to perform consistent estimation within a one-step GMM framework. Most recently Mollisi & Rovigatti (2017) proposed a new estimator, based on the Wooldridge approach, using dynamic panel instruments as used in the Blundell & Bond (1998) methodology. In this paper, we apply the Wooldridge TFP estimation approach.

To control for heterogeneous levels of ability, we estimate residuals from a Mincer equation, defined over traditional individual-level variables such as age, age squared, education and gender. We take this measure as our proxy for ability and calculate the average ability of the firm's workforce.

A growing number of studies shows the importance of corporate ownership structures on productivity and managerial practices. There are not only potential differences between foreign and domestic multinational firms, but also among the various categories of domestic firms. Our study separates firms in four ownership categories: domestic non-affiliated firms, domestic affiliated firm (UNE), and domestic and foreign multinationals.

Other controls included in our regressions are measures of firm size, industry-specific effects for 18 two-digit industries and time-specific effects. Table 8 in the Appendix lists all variables used in the analyses and provides detailed definitions for each of them.

3.1 Descriptive Statistics

The average annual number of firms observed in our study is about 7,500, and as shown in Table 1, this yields a total of 73,722 firm-year observations. There is substantial attrition, approximately 20%, in the sample, from 8,219 firms in 2001 to 6,569 firms in 2014. Most firms in our sample are domestic non-affiliated or independent companies (78%) located outside metropolitan or large cities (45%), have fewer than 50 employees (75%) and are categorized as low or medium-low technology companies (56%). Only 25% of the firms have fifty or more employees, and more than seven out of ten firms are are located in large cities or metropolitan areas. About half of the firms are classified as high or medium-high technology firms.

Figure 1 provides a snapshot of offshoring engagement across regions for the four different ownership categories. About two-thirds of manufacturing firms in our sample carry out offshoring. There is, however, a large variation in the sample. The upper part of the figure reports figures for multinational companies and the lower part for domestic companies. The MNE companies are divided into foreign-owned and domestically owned, while the domestic companies can be part of a group (Uninational) or be independent companies (Non affiliated). The importance of offshoring across destination regions appears to be similar between MNEs as well as between non-MNEs, but differs across these two categories of ownership. While around nine out of ten MNEs are contracting out production internationally, the corresponding figure for non-MNEs is about 50%. Most noticeable is the relative growth of offshoring destinations in Eastern Europe (all former non-market economies in Eastern Europe except Russia) in all four ownership categories. At the same time, it also appears that the proportion of companies that offshored production to the BRICS countries has decreased, especially among domestic MNEs, while it has increased to the counties we refer to as Rest of the World (ROW) in this study. While Figure 1 only shows offshoring as a fraction of firms, the intensity of offshoring is reported in Section 5,

Table 1: Descriptive Statistics for Swedish Manufacturing Firms, 2001–2014

	Freq.	Percent	Cum.
Ownership			
Foreign MNE	5,769	7.83	7.83
Domestic MNE	10,253	13.91	21.74
Domestic Non-affiliated	21,943	29.76	51.50
Domestic UNE	35,757	48.50	100.00
Region			
Metropolitan areas	13,324	18.07	18.07
Large cities	27,332	37.07	55.15
Rest of Sweden	33,066	44.85	100.00
Firm Size			
10-19 employees	31,686	42.98	42.98
20-49 employees	23,472	31.84	74.82
50-99 employees	9,225	12.51	87.33
≥100 employees	9,339	12.67	100.00
Technology Group			
High tech (HT)	3,757	5.10	5.10
Medium-high tech (MHT)	28,451	38.59	43.69
Medium-low tech (MLT)	26,640	36.14	79.82
Low tech (LT)	14,874	20.18	100.00
Total obs. (firm-years)	73,722		

Table notes: MNE stands for multinational enterprise and UNE domestic affiliated firm. Metropolitan areas are Stockholm, Gothenburg and Malmö. Large cities are those with more than 100,000 residents. Technology groups were defined according to the OECD classification from information on R&D and human capital intensity.

Table 2 .

Related to the potential impact of offshoring on labor market outcomes such as income inequality, visual inspection of Figure 2 suggests that as offshoring has increased, there has been a corresponding increase in the Swedish skill premium.

Figure 1: Offshoring across regions. Proportions of firms.

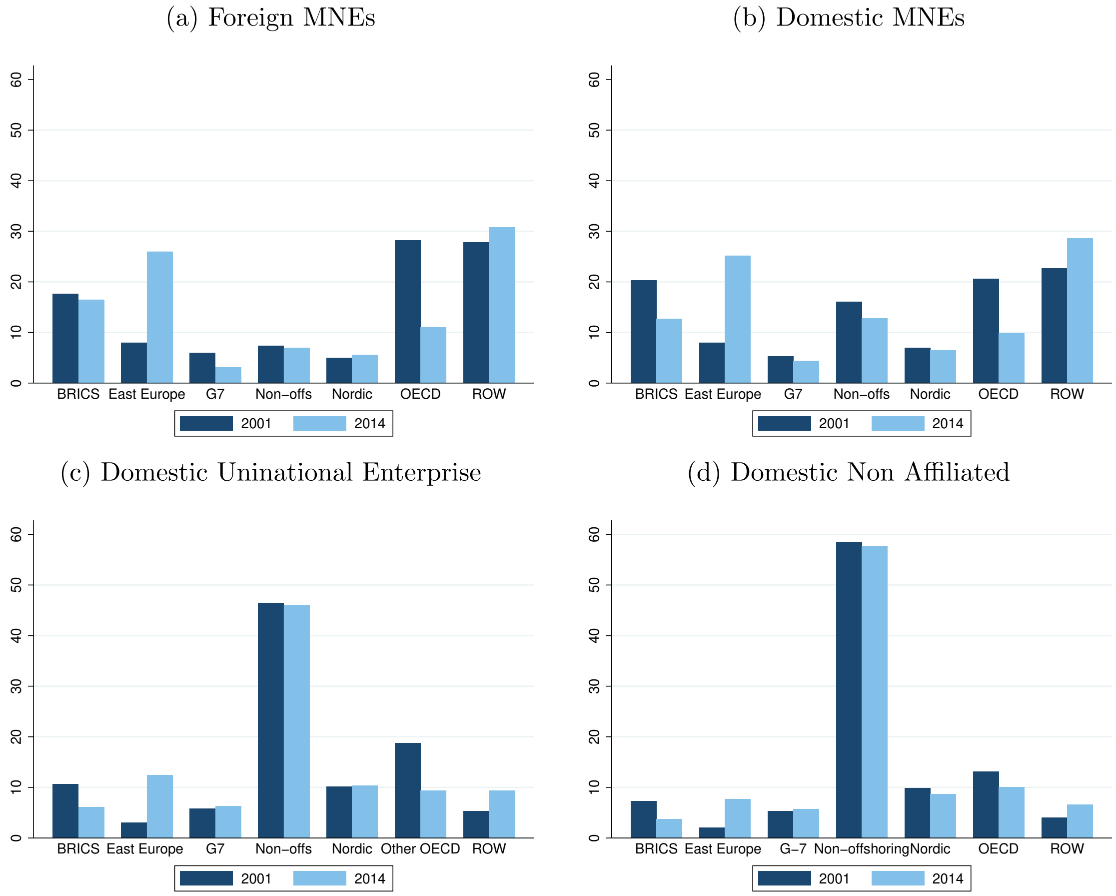

FIGURE NOTES: ***BRICS*** is Brazil, Russia, India China and South Africa. ***East Europe*** is all former non-market economies in Eastern Europe except Russia. ***G-7*** is U.S., Canada, U.K., France, Germany, Italy and Japan. ***Non-off*** refer to firms not offshoring production. ***Nordics*** is Finland, Denmark, Norway and Iceland. ***OECD*** is all OECD-members except G-7 and Nordic countries. ***ROW*** is all other countries.

Figure 2: Offshoring and the skill premium in Sweden

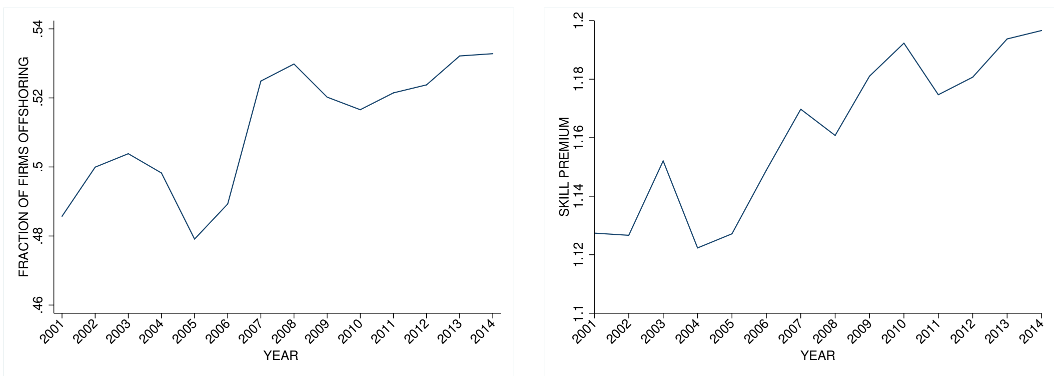

FIGURE NOTES: The left panel depicts the fraction of firms in Swedish manufacturing that utilize offshore production. The right panel plots the skill premium, defined as the wage ratio between university-educated and non-university educated workers, for the 75^{th} percentile. Both of these figures are based on firms with at least 10 employees.

4 Empirical Strategy

In order to estimate how the offshoring destination affects the likelihood of innovation, proxied by applying for a patent , we specify the following model:

$$
\begin{aligned}
Pr(\text{patent}_{it} = 1) \quad = \quad & f(\text{offshoring destination}_{it}, \text{potential offshorability}_{it}, \text{workers'} \\
& \text{ability}_{it}, \text{automation potential}_{it}, \text{controls}_{it}, \lambda_t, \mu_i, \epsilon_{it}) \qquad (1)
\end{aligned}
$$

where λ_t is a year effect, μ_i is a firm-specific error component and ϵ_{it} is an idiosyncratic error. This model is estimated as a random effects probit model.

Next, we estimate the impact of offshoring on the firm's productivity, expressed as log TFP, in a dynamic specification. This model is specified as

$$
\begin{aligned}
\log \text{TFP}_{i,t} \quad = \quad & f(\log \text{TFP}_{i,t-1}, \log \text{offshoring}_{it}, \text{potential offshorability}_{it}, \text{automation} \\
& \text{potential}_{it}, \text{workers' ability}_{it}, \text{controls}, \lambda_t, \mu_i, \epsilon_{it}) \qquad (2)
\end{aligned}
$$

To estimate this dynamic panel model specification, we employ the first-difference GMM estimator developed by Arellano & Bond (1991). This framework is convenient because it is relatively easy to allow for the endogeneity of offshoring, which is instrumented with both its own lagged level values together with other covariates. It should be noted, however, that we do not include any external instruments.

4.1 Propensity Score Matching

In this empirical analysis we focus on estimating the causal effect from offshoring on those firms that persistently offshore production. As we cannot observe the counterfactual for those firms that offshore, i.e. their outcomes if they had not chosen to offshore, we establish a quasi-experimental research design by defining a control group of non-offshoring firms which are most similar to the offshoring firms. To identify those firms we use propensity score matching, or PSM (Rosenbaum & Rubin 1984, Rubin 1997).[3] The first step in PSM is to estimate the likelihood of a firm to be a persistent offshoring firm, for which we use a

[3] Note that coarsened exact matching (CEM) would have been an alternative to PSM, which might be more robust as it does not rely on functional form specification (Iacus, King & Porro 2012). PSM is very convenient as it allows the inclusion of pre-treatment values of the outcome variables, which will balance the pre-treatment outcome variables between the groups. Very often, however, the results from these two matching approaches do not differ greatly.

probit model. This model is estimated based on variables for year 2001, while persistent offshoring is determined for the entire sample period.[4]

5 Empirical Results

In this section, we present summary statistics and estimates for the models specified in equations (1) and (2). We employ different estimation techniques in order to gauge the importance of offshoring on different aspects of firms' innovation strategies.

Table 2 reports summary statistics for key variables in the analysis. Five percent of the firms are protecting their innovations with formal intellectual rights (patent).[5] Total factor productivity is expressed in logarithms. We define employees with three years of university education as skilled employees, and those with a lower level of education as unskilled. On average, 7% of the employees in a firm are classified as skilled, and the mean skill premium is 0.75.

Our main offshoring measure is reported for all six destinations in the study. Normalizing offshore by by sales, the table reveals that the G-7 countries and other OECD countries are the most important destinations. We estimate a Mincer residual for each employee, assuming that it can be used as a proxy for ability as a complement to human capital.

Approximately 50% of jobs are potentially offshorable as expressed by the Blinder index. The Osborne–Frey index suggests that 60% of the jobs in Swedish manufacturing can potentially be replaced by machines or robots in the near future. We denote this measure as *Automation potential*, assuming that a high value of this index reflects unexploited efficiency potential.

[4] A persistent offshoring firm has offshoring of at least 10% relative to its sales and in at least 80% of the observation years. A non-offshoring firm is defined as a firm that has less than 5% offshoring relative to sales in all observation years. Thus, we are implicitly defining a hurdle model for offshoring with this specification.

[5] The patent measure may be compared with the self-declared innovation measured in the Eurostat Community Innovation Survery (CIS) where firms report whether they have introduced a good or a service new for the firm or new for the market. According to CIS 2016, almost one third of the Swedish firms declared themselves as innovative.

Table 2: Summary statistics

Variable	Obs.	Mean	SD	50^{th} percentile	Min	Max
Patent applications	73,722	0.05	0.22	0	0	1
log TFP	73,722	14.17	0.60	14.09	12.65	15.94
Human capital	73,722	0.07	0.11	0.04	0	1
Skill premium	73,719	0.75	0.82	0.69	0	10.82
Offshoring to Nordics	73,722	0.010	0.034	0	0	0.218
Offshoring to G-7	73,722	0.030	0.070	0	0	0.380
Offshoring to other OECD	73,722	0.017	0.045	0	0	0.262
Offshoring to BRICS	73,722	0.006	0.023	0	0	0.149
Offshoring to Eastern Europe	73,722	0.003	0.012	0	0	0.084
Offshoring to rest of the world	73,722	0.001	0.005	0	0	0.037
Workers' ability	73,722	-0.07	0.17	-0.06	-2.05	1.10
Potential offshorability	72,761	0.51	0.16	0.55	0	0.94
Automation potential	72,761	0.59	0.14	0.58	0.01	0.98

Table notes: The patent application variable is assumed to be an indicator of innovation activity. Human capital is defined as the share of university-educated workers in total employment. The skill premium is the ratio of wages of university-educated to non-university educated workers. Offshoring to destination r is proxied by the value of imported intermediate goods relative to sales. Workers' ability is the Mincer residual. Potential offshorability and automation potential are the computed Blinder and Frey–Osborne indexes, respectively.

5.1 Innovation and technical change

Table 3 reports average marginal effects of the propensity to apply for patents. A priori, we assume that offshoring allows firms to switch resources from production to research. The working hypothesis is that this should be manifested through increased innovation capabilities. The hypothesis is confirmed for offshoring to low wage destinations (Eastern Europe and Rest of the World), and partly for offshoring to *other OECD countries* (MTL and LT).

Our second analysis considers total factor productivity as a measure of technical change. Some of the prior empirical literature reports a positive impact of offshoring on TFP. However, what distinguishes our analysis from most of the existing literature is that we observe the entire universe of manufacturing firms in the economy, both small, middle-sized and large, over a long period. In addition, we are able to control for a number of company and employee characteristics in order to identify the impact of offshoring.

Table 4 presents results from four different dynamic models: pooled OLS, fixed effects, difference GMM and system GMM. The two latter are estimated by the Arellano–Bond approach. In this analysis, we measure offshoring by the logarithm of its nominal value.

The approaches presented in columns (1) and (2) show a positive and highly significant association between offshoring and TFP. However, both the pooled OLS and fixed effects estimates are potentially Nickell-biased in a dynamic setting. Columns (3) and (4) present results from the Arellano–Bond instrumental variable estimator for the dynamic panel setting which allows for a causal interpretation of the estimates. Both columns show positive and highly significant coefficients on the offshoring variable. The size of the coefficient estimate is 0.011 in the difference GMM model and 0.022 in the system GMM model.

The test statistics in the foot of the table show that the instruments are valid in both Arellano–Bond estimators and that there is no second-order serial correlation in the differenced error terms.

The overall results in the first step of the analysis provide a positive link between global value chains, as reflected by an increased reliance on offshoring, and innovation and technical change. It should be noted that we may only interpret this relationship

Table 3: Patent applications, average marginal effects

	(1) All firms	(2) HT and MHT	(3) LHT and LT	(4) All firms	(5) HT and MHT	(6) LHT and LT
Offshoring destination:						
All regions	0.0299***	0.0205	0.0343***			
	[0.0097]	[0.0180]	[0.0094]			
Nordics				-0.0054	0.0045	-0.0170
				[0.0298]	[0.0566]	[0.0271]
G-7				0.0184	0.0204	0.0217*
				[0.0132]	[0.0222]	[0.0129]
Other OECD				0.0141	-0.0468	0.0378**
				[0.0209]	[0.0429]	[0.0188]
BRICS				0.0057	0.0830	-0.0471
				[0.0434]	[0.0681]	[0.0437]
Eastern Europe				0.2921***	0.3597***	0.2800***
				[0.0611]	[0.1089]	[0.0622]
Rest of the world				0.2899**	0.2893	0.2700*
				[0.1477]	[0.2603]	[0.1494]
Key controls:						
Potential offshorability	0.0003***	0.0002	0.0003***	0.0003***	0.0002	0.0003***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Workers' ability	0.0473***	0.0654***	0.0363***	0.0476***	0.0666***	0.0362***
	[0.0067]	[0.0125]	[0.0070]	[0.0067]	[0.0124]	[0.0069]
Automation potential	-0.0363***	-0.0639***	-0.0214***	-0.0356***	-0.0640***	-0.0208***
	[0.0068]	[0.0125]	[0.0069]	[0.0068]	[0.0125]	[0.0069]
Firm size:						
30-49 employees	0.0100***	0.0153***	0.0070***	0.0101***	0.0153***	0.0073***
	[0.0018]	[0.0033]	[0.0019]	[0.0018]	[0.0033]	[0.0019]
50-99 employees	0.0385***	0.0582***	0.0209***	0.0380***	0.0574***	0.0212***
	[0.0037]	[0.0062]	[0.0038]	[0.0037]	[0.0062]	[0.0037]
$\geq$ 100 employees	0.0946***	0.1463***	0.0630***	0.0938***	0.1438***	0.0631***
	[0.0063]	[0.0109]	[0.0064]	[0.0063]	[0.0108]	[0.0063]
Firm location:						
Large cities	-0.0020	-0.0052	-0.0010	-0.0022	-0.0055	-0.0011
	[0.0037]	[0.0060]	[0.0039]	[0.0037]	[0.0060]	[0.0039]
Rest of Sweden	0.0074**	0.0122*	0.0044	0.0073**	0.0123*	0.0042
	[0.0037]	[0.0063]	[0.0038]	[0.0037]	[0.0063]	[0.0039]
Technology group:						
MHT	0.0048	-0.0055		0.0045	-0.0056	
	[0.0045]	[0.0068]		[0.0045]	[0.0067]	
MLT	-0.0024			-0.0024		
	[0.0043]			[0.0043]		
LT	-0.0141***		-0.0083***	-0.0138***		-0.0082***
	[0.0044]		[0.0026]	[0.0044]		[0.0026]
Observations	72,761	31,779	40,982	72,761	31,779	40,982

Cluster-robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table notes: Estimation is for panel-data, random-effects probit models. Dependent variable is a dichotomous variable for patenting. Non-offshoring firms, firms with 10-29 employees, foreign MNEs, firms located in Metropolitan areas and High-tech firms (HT) constitute the reference groups. The measure for potential offshorability is the firm-specific computed Blinder index. The measure for ability is the firm-specific, fully-saturated Mincer residual. The measure for automation potential is the firm-specific Frey–Osborne index. Measures of offshoring are winsorized to exclude the 1% extreme values of the upper tail of the distribution. Regressions include ownership, firm and time fixed effects.

in terms of causality with regard to the effect on TFP. Further, as we do not use any external instruments in the Arellano-Bond model, the results should be interpreted with some caution.

In the next step of the analysis, we test the sensitivity of the parameter estimates above in an approach that accounts for self-selectivity and reverse causality between innovation and productivity.

5.2 Robustness test

It is plausible that firms that are more productive and have higher innovation capabilities are more likely to engage in offshoring activities. In this case high productivity and high innovation capability jointly determine the likelihood and intensity of offshoring. In fact, the results from the PSM shown in Table 6 imply that persistent offshoring firms, in our case about 1,000 of the 7,000 firms in the sample, have more patents and significantly higher productivity compared to non-offshoring firms. However, it is an open question whether this is a result of offshoring or itself a determinant of the likelihood to engage in offshoring.

With the help of PSM we can define a control group of non-offshoring firms which are most similar to the offshoring firms in their productivity and innovation outcomes in 2001. The results of Table 6 indicate that there are no remaining significant differences between the treatment group of offshoring firms and those in the control group after matching.

We then study the outcome variables, patent applications and TFP, for 2002–2014 for these two groups of firms. Table 7 presents estimates for the matched sample. Probit estimates for the innovation model are reported in columns 1 and 2. While we found highly significant and positive point estimates for the category *all firms* in Table 3, the pooled probit estimate results in column 1 are still positive but no longer significant. Column 2 considers a panel probit model using the random effect estimator. The effect of offshoring on innovation is positive, but only at the 90% level of significance. Thus, after accounting for self-selectivity, the treatment effects from offshoring become much weaker in the preferred random effects model.

Columns 3 and 4 reveal the causal impact of offshoring on TFP using the matched sample of offshoring and non-offshoring firms. Not accounting for self-selection and not properly controlling for endogeneity, the dynamic Arellano-Bond estimates in Table 4 supported the literature that suggests that firms which replace in-house production of intermediate inputs with insourcing from foreign destinations increase their productivity. Although this effect remains in the pooled OLS model reported in column 3, the effect disappears completely when we include firm fixed effects in the preferred TFP model presented in column 4.

Taken together, the matching results imply that offshoring is clearly endogenous, with self-selection as an important factor that should be addressed in the empirical approach. Most of the previous research has neglected this issue.

Table 4: Offshoring and total factor productivity (log TFP)

	(1) OLS	(2) Fixed effects	(3) Diff. GMM	(4) Syst. GMM
log TFP$_{t-1}$	0.7203***	0.2469***	0.2673***	0.2684***
	[0.0070]	[0.0099]	[0.0206]	[0.0209]
log Offshoring	0.0105***	0.0154***	0.0119***	0.0229***
	[0.0006]	[0.0013]	[0.0018]	[0.0045]
KEY CONTROLS:				
Potential offshorability	-0.0000	-0.0004**	-0.0001	-0.0001
	[0.0001]	[0.0002]	[0.0002]	[0.0002]
Workers' ability	0.2757***	0.1513***	0.0757***	0.0733***
	[0.0137]	[0.0202]	[0.0234]	[0.0234]
Automation potential	-0.1032***	-0.0141	0.0395	0.0395
	[0.0135]	[0.0210]	[0.0252]	[0.0253]
FIRM SIZE:				
30-49 employees	0.0543***	0.0526***	-0.0132	-0.0165
	[0.0042]	[0.0087]	[0.0211]	[0.0211]
50-99 employees	0.1130***	0.1095***	-0.0262	-0.0327
	[0.0059]	[0.0132]	[0.0260]	[0.0262]
$\geq$ 100 employees	0.2203***	0.1591***	-0.0488	-0.0572
	[0.0087]	[0.0195]	[0.0347]	[0.0349]
OWNERSHIP:				
Domestic non-affiliated			0.0161	0.0170
			[0.0187]	[0.0187]
Domestic UNE	0.0014	0.0004	0.0086	0.0091
	[0.0039]	[0.0083]	[0.0152]	[0.0152]
Domestic MNE	0.0066	0.0025		
	[0.0057]	[0.0135]		
FIRM LOCATION:				
Large cities	-0.0081*	0.0813	0.0853	0.0835
	[0.0047]	[0.0742]	[0.0908]	[0.0905]
Rest of Sweden	0.0000	0.0302	-0.0032	-0.0047
	[0.0047]	[0.0717]	[0.0725]	[0.0724]
TECHNOLOGY GROUP:				
MHT	-0.0255***	-0.0118	-0.0251	-0.0248
	[0.0066]	[0.0116]	[0.0191]	[0.0191]
MLT	-0.0288***	-0.0257**	0.0004	0.0003
	[0.0065]	[0.0108]	[0.0200]	[0.0200]
LT	-0.0379***	-0.0392***	-0.0090	-0.0088
	[0.0067]	[0.0109]	[0.0183]	[0.0183]
Observations	39,047	39,047	30,329	30,329
Firms	6,938	6,938	5,408	5,408
Instruments			39	42
Hansen J p-value			0.352	0.256
AR(2) p-value			0.933	0.994

Cluster-robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE NOTES: Estimation method is reported underneath the column number. Dependent variable is total factor productivity (TFP), calculated à la Wooldridge (2009). The difference between columns (3) and (4) is that offshoring is treated as endogenous in the latter. Firms with 10-29 employees, foreign MNEs, high-tech firms and firms located in Metropolitan areas are the reference groups. Important to note is that we estimate with an absolute measure of offshoring (this avoids having productivity shocks artificially caused by sales movements). The measure for potential offshorability is the firm-specific computed Blinder index. The measure for ability is the firm-specific, fully-saturated Mincer residual. The measure for potential offshorability is the firm-specific computed Blinder index. The measure for automation potential is the firm-specific Frey-Osborne index. All regressions include firm- and time-specific effects, with the sole exception of OLS which does not include firm-specific effects.

Table 5: Determinants of the likelihood of being a persistent offshoring firm, PSM

	(1) pr(offshoring=1)
patent	0.164*
	[0.090]
log TFP	0.257***
	[0.057]
Domestic non-affiliated	0.490***
	[0.066]
Domestic UNE	0.991***
	[0.072]
Domestic MNE	-0.126**
	[0.063]
30-49 employees	0.181***
	[0.060]
50-99 employees	0.523***
	[0.078]
$\geq$ 100 employees	0.441***
	[0.097]
MHT	-0.695***
	[0.098]
MLT	-0.461***
	[0.103]
LT	-0.187*
	[0.106]
Large cities	0.148**
	[0.070]
Rest of Sweden	0.153**
	[0.068]
Potential offshorability	0.001
	[0.001]
Automation potential	-0.142
	[0.147]
Human capital	-0.569**
	[0.283]
# firm obs in panel	0.031***
	[0.005]
Constant	-4.761***
	[0.797]
Observations	4766

Notes: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Offshoring refers to firms that have at least 10% offshoring relative to sales in at least 80% of observation years 2001-2014.

Table 6: Tests of balancing assumption after propensity score matching, year 2001

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct —bias—	t-test t	p> $\|t\|$
patent	U	0.12171	0.04039	30.1		9.98	0
	M	0.12171	0.10419	6.5	78.4	1.25	0.21
log TFP	U	14.452	13.977	82.1		24.65	0
	M	14.452	14.379	12.6	84.7	2.7	0.007
Potential offshorability	U	50.702	51.086	-1.9		-0.55	0.582
	M	50.702	50.543	0.8	58.7	0.19	0.853
Automation potential	U	0.59512	0.59874	-2.1		-0.58	0.561
	M	0.59512	0.58787	4.3	-100.4	0.98	0.329
Human capital	U	0.06709	0.04827	21		5.62	0
	M	0.06709	0.07136	-4.8	77.3	-1.03	0.301
# firm obs in panel	U	9.6164	8.7248	18.9		5.33	0
	M	9.6164	8.9542	14	25.7	3.22	0.001
Domestic non-affiliated	U	0.30867	0.15485	37.1		11.32	0
	M	0.30867	0.38851	-19.2	48.1	-3.81	0
Domestic UNE	U	0.35054	0.07301	72.2		24.64	0
	M	0.35054	0.25609	24.6	66	4.68	0
Domestic MNE	U	0.14411	0.42525	-65.5		-17.08	0
	M	0.14411	0.13437	2.3	96.5	0.64	0.524
30-49 employees	U	0.18987	0.48596	-65.9		-17.55	0
	M	0.18987	0.19279	-0.7	99	-0.17	0.866
50-99 employees	U	0.26874	0.33458	-14.4		-4.01	0
	M	0.26874	0.3184	-10.8	24.6	-2.47	0.013
$\geq$ 100 employees	U	0.22882	0.10083	35		10.99	0
	M	0.22882	0.24927	-5.6	84	-1.09	0.278
MHT	U	0.39143	0.5579	-33.8		-9.55	0
	M	0.39143	0.41383	-4.5	86.5	-1.03	0.301
MLT	U	0.29017	0.24124	11.1		3.2	0.001
	M	0.29017	0.29698	-1.5	86.1	-0.34	0.735
LT	U	0.21616	0.17037	11.6		3.39	0.001
	M	0.21616	0.20935	1.7	85.1	0.38	0.706
Large cities	U	0.34956	0.35357	-0.8		-0.24	0.812
	M	0.34956	0.35151	-0.4	51.4	-0.09	0.926
Rest of Sweden	U	0.51899	0.46028	11.8		3.34	0.001
	M	0.51899	0.52191	-0.6	95	-0.13	0.895

Table 7: Causal impact of offshoring on outcome variables patent and TFP, matched samples of offshoring and non-offshoring firms, years 2002-2014

	(1) probit pr(patent)	(2) probit RE pr(patent)	(3) pooled OLS log TFP	(4) FE (DiD) log TFP
persistent offshoring$_i$=1	0.015	0.199*	0.044***	
	[0.031]	[0.105]	[0.016]	
offshoring$_{it}$=1				0.016
				[0.042]
30-49 employees	0.279***	0.495***	0.252***	0.115***
	[0.067]	[0.129]	[0.022]	[0.019]
50-99 employees	0.504***	0.910***	0.494***	0.201***
	[0.068]	[0.145]	[0.024]	[0.024]
$\geq$ 100 employees	1.061***	1.533***	0.950***	0.298***
	[0.066]	[0.150]	[0.027]	[0.032]
Domestic non-affiliated	0.402***	0.319***	0.115***	-0.013
	[0.051]	[0.106]	[0.019]	[0.018]
Domestic UNE	0.225***	0.100	0.125***	-0.006
	[0.053]	[0.117]	[0.020]	[0.023]
Domestic MNE	0.139*	0.186	-0.003	0.009
	[0.079]	[0.141]	[0.024]	[0.018]
Potential offshorability	0.007***	0.005**	0.000	-0.000
	[0.001]	[0.002]	[0.000]	[0.000]
Automation potential	-0.277**	0.006	-0.120**	0.011
	[0.137]	[0.275]	[0.053]	[0.038]
Human capital	2.956***	3.211***	1.757***	1.339***
	[0.140]	[0.368]	[0.077]	[0.102]
MHT	0.392***	0.348***	-0.022	0.003
	[0.057]	[0.111]	[0.028]	[0.021]
MLT	0.094	0.251**	-0.021	-0.001
	[0.059]	[0.102]	[0.026]	[0.019]
LT	-0.264***	-0.218*	-0.052**	-0.055***
	[0.071]	[0.123]	[0.026]	[0.021]
Large cities	-0.034	-0.075	-0.010	-0.067
	[0.046]	[0.160]	[0.026]	[0.138]
Rest of Sweden	-0.028	-0.066	-0.001	-0.159
	[0.045]	[0.155]	[0.025]	[0.135]
Constant	-2.751***	-4.234***	13.865***	14.354***
	[0.137]	[0.295]	[0.054]	[0.119]
FE year	yes	yes	yes	yes
FE firm	no	no	no	yes
RE firm	no	yes	no	no
ln σ_u^2		0.879***		
		[0.085]		
Observations	16536	16536	16536	14717

Notes: Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
FE=fixed effects, RE=random effects, DiD=difference-in-difference estimator

6 Conclusion

The rapid growth of offshoring in production and service tasks that were previously produced domestically is a key feature of the global economy over the last three decades. However, understanding how offshoring affects firms' innovation and technical change remains an important question in economics. Recent theoretical development and empirical studies yield ambiguous conclusions. While one group of studies provides evidence supporting important efficiency and specialization gains from this internal resource allocation, other authors question the positive effects of offshoring and argue that separating the production and development functions of a firm can undermine its innovation capacity and hinder its productivity growth.

This paper contributes to the literature by performing an empirical investigation that addresses some of the shortcomings in previous studies. We study the universe of manufacturing companies in an industrialized economy. The data allow us to observe the firms and their employees over a 14 year period. By observing detailed business characteristics for all companies in the economy, we are able to deal with both selection and simultaneity issues, using a control group and appropriate econometric techniques.

There are two main results from our analysis of Swedish manufacturing firms. First, without accounting for self-selection into offshoring and properly controlling for endogeneity, the estimates suggest that innovation, measured by patent applications and total factor productivity, is an increasing functions of offshoring. Second, applying a matching approach with a control group of similar firms, our estimates show that this positive link is largely explained by self-selection and reverse causality. Controlling for both sources of bias, we find no causal impact of offshoring on TFP. The positive impact of offshoring on innovation remains, but at a low level of statistical significance.

Our results are consistent with the trade literature that finds that exporters are on average more productive than other firms, and that self-selected exporters are more innovative. A growing number of studies fail to find strong evidence for positive effects of exporting on firm performance.[6] In line with these findings, we do not find evidence of a strong causal relationship between offshoring and firms' innovation and productivity once

[6] See for instance (Bernard & Jensen 1999, Máñez-Castillejo, Rochina-Barrachina, Sanchis-Llopis et al. 2009, Temouri, Vogel & Wagner 2013, Greenaway & Kneller 2007).

the endogeneity of the offshoring decision is considered in the empirical approach. Areas for future study may include assessing the relevance of this conclusion for companies in different size classes, different industries, different offshoring destinations and different ownership connections to foreign suppliers of intermediate inputs.

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Appendix

Table 8: Variable definitions

Variable	Measure	Definition
Innovation	dummy	Dichotomous variable of patenting (patenting= 1; 0, otherwise)
TFP	continuous	Calculated according to Wooldridge (2009)'s approach
Human capital	continuous, relative	Ratio of university-educated workers to total employment
Skill premium	continuous, relative	Avg. wage ratio of university-educate to non-university educated workers
Offshoring	continuous	Monetary value of the intermediate goods imported
Offshoring to r	continuous, relative	Ratio of the monetary value of the imported intermediate goods from region r to total intermediate imports
Potential offshorability	continuous	Fraction of offshorable jobs, calculated as the Blinder & Krueger (2013) index
Workers' ability	continuous	Avg. workforce ability, calculated as the Mincer residual
Automation potential	continuous	Fraction of potentially automated jobs, calculated as the Frey & Osborne (2017) index
Firm size	discrete	Defined over five groups depending on the number of employees
Ownership category	discrete	Defined over four categories attending to ownership's origin (domestic vs. foreign) and type of business entity (non-affiliated, UNE, MNE)
Technology group	discrete	Defined over four categories (high, medium-high, medium-low, low) attending to R&D and human capital intensity
Firm location	discrete	Defined over three categories attending to population density (Metropolitan area, large cities, rest of Sweden)

Table notes: Continuous variables are absolute measures except indicated otherwise.