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Swedish Manufacturing**

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# Offshoring and Innovation Capabilities: Evidence from Swedish Manufacturing<sup>☆</sup>

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## Abstract

This paper examines the impact of global value chains on firms' innovation capabilities. Using the United Nations Broad Economic Categories (BEC) system to identify offshoring-related intermediate imports, we study contracting out production over the period 2001–2014 from about 7,000 mainly small Swedish manufacturing firms to six different destinations and test hypotheses on improvements and outcomes of innovation capabilities. Our empirical findings show that the strategy to participate in global value chains increases firms' innovative capability regardless of firms' technology intensity. The results are robust to a wide set of controls and in line with predictions in recent models of directed technical change.

*Keywords:* Offshoring, Innovation Capabilities, Technical Change, Skill Premium, Panel Data

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## 1. Introduction

The existing literature on global value chains has analyzed how offshoring affects productivity, wages and employment. Theory predicts that firms should generate higher productivity due to redistribution of labor and capital, increase wage differences associated with the process of skill-biased technical change, reduce low-skilled jobs and possibly increase high-skilled jobs. A comprehensive empirical literature has largely confirmed several of these hypotheses at the aggregate level. In contrast, the evidences at the firm level are mixed. Several explanations are suggested: researchers cannot systematically identify offshoring at the firm level (Olsen, 2006); the impact of offshoring might be indirect rather than direct (Akhmetova and Ferguson, 2015); or the causality between offshoring and firm performance is difficult to sort out empirically (Bernard and Jensen, 1999).

Innovation is a key driver of the emergence of global value chains and the fragmentation of production. Research on how offshoring affects companies' innovation capacity is very limited. Some important key issues discussed in this sparse literature are how spatial separation of manufacturing and R&D affects innovation capability (Narula, 2014), and whether outsourcing enables firms to focus their resources on activities where they have comparative advantage and increase their innovative activities (Bloom, Draca and Van Reenen, 2016).

Outsourcing of business activities is by no means a new economic phenomenon, as it has been prevalent since the early days of industrial development. The intensity, however, increased rapidly in recent decades. With the advent of offshoring in the 1990s, a new phase of the contracting out phenomenon was introduced. Explanations for this development consider several key factors: technological advances, institutional developments favoring trade liberalization and competitive pressures to reduce costs, and improved productivity (Olsen, 2006). The single most important factor is the digitalization 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. [Porter \(1985\)](#) compares this value-chain process with the Ricardian principle of comparative advantage. In line with the theoretical foundations of [Coase \(1937\)](#), he suggests that firms can increase their productivity by focusing on what they do best and outsource the rest.

As noted in the previous literature, it is difficult for the researcher to observe offshoring at the firm level in a systematic way that allows for comparison across firms and across time. As offshoring is part of 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 and Schott \(2012\)](#) and further developed by [Van Beveren, Bernard and Van denbussche \(2012\)](#) for concordancing trade and production data over time, and consider an imported product as offshored if it is classified as an intermediate good.

The aim of this paper is to contribute to the literature on the impact of global value chains on firm innovation. To do so, we examine the relationship between offshoring defined by the BEC and firms' technological innovation capabilities. Following prior studies, we consider these capabilities as a set of special assets including knowledge, technology, products, processes, experience, and organization that facilitates and supports innovation ([Yam, Guan, Pun and Tang, 2004](#)). We study offshoring to six different destinations and test hypotheses on improvements and outcomes of innovation capabilities. We first estimate the marginal effect of increased offshoring on skill composition and return on skills. Next, we examine the relationship between offshoring and patents and technical change, respectively.

Overall, our empirical findings show that firms' innovation capacity benefits from

global value chains. We also document heterogeneity in the results with respect to offshoring destinations and categories of innovation capability.

The rest of the paper is structured as follows. Section 2 briefly surveys the relevant literature and sets forth the hypotheses of interest. 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. Literature Review and Hypotheses

The economic literature on the relationship between global value chains and innovation is dominated by studies on R&D and productivity. Many studies focus on multinational firms (MNE) and foreign direct investments (FDI). For example, [Kuemmerle \(1999\)](#), uses data from 136 laboratory investments in 32 MNEs to explore determinants to FDI in R&D. He finds that the relative market size and relative strengths of the scientific base are important in improving existing innovation capabilities or for building new firm-specific capabilities.

[Steinberg et al. \(2017\)](#) distinguishes between R&D offshoring to foreign affiliates and external foreign parties and finds that both offshoring strategies eventually harm firms' innovation performance when excessively employed. The analysis of [Hurtado-Torres, Aragón-Correa and Ortiz-de Mandojana \(2017\)](#) considers how geographical diversification of firms' R&D offshoring affects their innovation performance. Using data from 110 MNEs in the energy industry, the authors suggest that an inverted U-shape pattern exists.

An empirical issue when trying to assess the impact of contracting out research or production activities on innovation performance is how innovation can be observed. Prior studies often used R&D as a proxy, while the increased availability of extensive firm-level data allows for other alternatives. Successful innovation performance can be related to firms' innovation capability which consists of several different factors. [Adler and Shenhar \(1990\)](#) define innovation capabilities as: (1)

the capacity of developing new products satisfying market needs, (2) the capacity of applying appropriate process technologies to produce these new products, (3) the capability of satisfying future needs by developing and introducing new products and new process technology, and (4) the capability to respond to an unanticipated technological change brought about by competitors and unforeseen circumstances. With this definition, innovation capabilities include a broad set of factors that range from supporting innovative activities to innovative outcomes.

By focusing on innovation capabilities instead of innovation, the analysis of the effects of offshoring can be extended to include a broad set of factors that support innovative activities and innovative outcomes. One of them is total factor productivity (TFP), which can be considered as the ultimate outcome measure of innovation capabilities (Hall, 2011). The relationship between offshoring and TFP has been studied in a number of papers (see Feenstra and Hanson, 1999, Egger and Egger, 2001, Head and Ries, 2002, Kimura, 2002, Hijzen, Grg and Hine, 2003, Tomiura, 2005, Hijzen, 2007).

Innovation capabilities can also be linked to the growing literature on directed- and trade-induced technical change (DTC) (see Acemoglu, 1998, 2002, Acemoglu and Zilibotti, 2001, Acemoglu, Gancia and Zilibotti, 2015, Burstein and Vogel, 2010, Bloom, Draca and Van Reenen, 2016). This literature argues that technical change is not neutral, but rather biased towards certain factors of production.

More recent DTC frameworks have placed offshoring at the center of the model in order to explore how it affects not only the direction and the bias of technical change but also inequality within and across countries. For example, Burstein and Vogel (2010) construct a model of international trade and offshoring that features the Stolper–Samuelson effect, implying that the skill premium in skill-abundant countries increases while it is reduced in skill-scarce countries. The latter is counteracted by a skill bias of technology that ultimately increases the skill premium in developing, skill-scarce countries.

A recent contribution to the literature on DTC and trade is [Bloom, Draca and Van Reenen \(2016\)](#), who argue that trade with less-developed countries such as China induces technological change, diffusion and upgrading across firms. In a broad sense, increased import competition forces domestic firms to be more productive in order to ensure survival in an environment in which firms from developing countries benefit from cheaper factors of production: in this case unskilled labor. In a more subtle sense, increased self-inflicted trade may have substantial effects within firms. [Bloom et al. \(2016\)](#) argue that if firms can liberate “trapped” factors of production through offshoring, they can concentrate on innovation, which may have compositional effects in the labor force. Other channels through which trade may induce technical change include the diffusion of knowledge which is embodied in intermediate capital goods.

In summary, the prior literature on offshoring and innovation is largely focused on issues around multinational firms, foreign direct investment and the separation of research and production. More recent studies provide a richer theoretical framework for the analysis which also motivates researchers to broaden the perspective from innovation to innovation capabilities. Guided by this literature, our paper studies how global contracting out of production processes influences the skill composition of workers, the skill premium, patents and technical change expressed by total factor productivity. To do this, we test the following hypotheses:

**H1:** There are compositional effects on employment associated with offshoring. Offshoring allows firms to increase the relative abundance of skilled labor.

**H2** There is a positive association between offshoring and the skill premium. This hypothesis corresponds to the case of [Acemoglu, Gancia and Zilibotti \(2015\)](#) in which, for initial low levels of offshoring, the skill premium increases as a consequence of higher offshoring, which reinforces the bias of technical change in the direction of skilled labor.

**H3:** Offshoring is positively associated with innovation capabilities. As suggested by [Bloom, Draca and Van Reenen \(2016\)](#), offshoring may translate into higher innovation levels when firms free up labor from production and are able to more intensively concentrate on innovation.

**H4:** Offshoring is positively associated with total factor productivity at the firm level. By contracting out certain less-efficient tasks, firms can increase productivity.

### 3. Data

The data come from two 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, since 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) and the OECD. By further merging these data with the employee dataset, we can access information on employees' level of education, occupation and income levels.

We calculate our offshoring measures based in the UN Broad Economic Categories (BEC) classification system to distinguish intermediate goods from other imports. Similar to the prior literature, intermediate imports are used as a proxy for offshoring.

We use two measures of offshoring. The first is intermediate imports normalized by sales, while the other is the nominal value of offshoring. We apply the first mea-



sure when estimating the impact on skill composition, skill premium and patenting. In the TFP estimation we apply the second definition.

To mitigate possible bias due to spurious correlation, we control for the potential trends that may make jobs more likely to be offshored,<sup>1</sup> using the Blinder index on offshorability.<sup>2</sup> Applying the classification method proposed by [Blinder and 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 and Osborne, 2017](#)) in our analyses. This index is supposed 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.

The main challenge in estimating total factor productivity (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 development of TFP computation addressing this bias ([Olley and Pakes, 1996](#), [Levinsohn and Petrin, 2003](#), [Akerberg, Caves and Frazer, 2006, 2015](#), [Manjiv and Maetz, 2016](#)). [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#), and [Akerberg et al. \(2006\)](#) contributed to the literature proposing two-step estimation procedures, while [Wooldridge \(2009\)](#) showed how to perform a consistent estimation within a single-step GMM frame-

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

<sup>2</sup>[Blinder and 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.

work. Most recently [Mollisi and Rovigatti \(2017\)](#) proposed a new estimator, based on the Wooldridge approach, using dynamic panel instruments as used in the [Blundell and Bond \(1998\)](#) methodology. In this paper, we apply the Wooldridge TFP approach.

To control for heterogeneous levels of ability, we estimate residuals from a fully-saturated Mincer equation, defined over traditional individual 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: non-affiliated domestic firms, uninational domestic firms (UNE), and domestic and foreign multinational firms (MNEs).

Other controls included in our regressions are measures of firm size, industry-specific effects for 18 two-digit industries and time-specific effects. [Table 7](#) in the Appendix lists all variables used in the analyses and provides detailed definitions for each of them.

### *3.1. Descriptive Statistics*

As shown in [Table 1](#), the average annual number of firms observed is about 7,500, which amounts to 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 (83%) located in non-metropolitan areas (82%), have fewer than 30 employees (60%) and are categorized as low or medium-low technology companies (57%). Only 18% of the firms are multinationals, have fifty or more employees and are located in metropolitan areas. More interestingly, only about 5% are high-technology firms. See [Table 2](#) for more detailed descriptive statistics.

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

|                         | FREQ.  | PERCENT | CUM.   |
|-------------------------|--------|---------|--------|
| <b>Ownership</b>        |        |         |        |
| 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 |
| <b>Region</b>           |        |         |        |
| 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 |
| <b>Firm Size</b>        |        |         |        |
| 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 |
| <b>Technology Group</b> |        |         |        |
| 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 for uni-national enterprise. Metropolitan areas are Stockholm, Gothenburg and Malmö, and large cities are those with more than 100,000 residents. Technology groups were defined according to the OECD classification by taking information on R&D- and human capital intensity.

About two out of three manufacturing firms in our samples carry out offshoring (see panel (a) in Figure 1). Most firms offshore to OECD countries, (excluding the G7), other Nordic countries and the BRICS at the beginning of the sample (see Panel (b) in Figure 1). There is, however, a substantial shift towards Eastern Europe<sup>3</sup> and other less-developed countries which jointly account for 50% of all offshoring in 2014, in comparison to the 20% recorded at the beginning of the sample period. When we consider the relative size of offshoring instead of fraction of offshoring firms, Table 2 shows that the OECD countries have a dominant role.

Figure 2 provides a snapshot of offshoring patterns and intensity across regions for the four different ownership categories. The relative importance of regions ap-

<sup>3</sup>The terms Eastern Europe and Soviet area are used interchangeably in this paper.

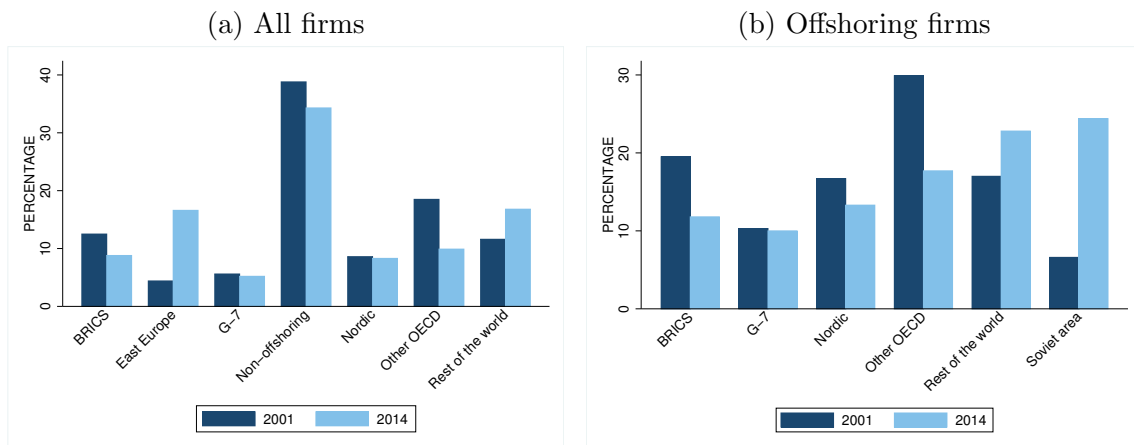


Figure 1: Offshoring Prevalence and Destination

FIGURE NOTES: BRICS are Brazil, Russia, India, China and South Africa. G-7 includes Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. Nordic Countries are Denmark, Finland, Iceland and Norway. Other OECD countries are all OECD countries except those in G-7. Soviet area considers all former members of the Soviet Union with the exception of Russia.

pears to be heterogeneous overall, but homogeneous across groups (MNEs vs. non-MNEs). Most noticeable is the relative growth of offshoring to Eastern Europe for all firms, although other less-developed countries have also benefited, as captured by “rest of the world”. Offshoring intensity varies from 93% in foreign MNEs to 42% in domestic non-affiliated companies.

Related to the potential impact of offshoring on labor market outcomes such as income inequality, visual inspection of Figure 3 suggests that as offshoring has increased, there has an increase in the Swedish skill premium. Another relevant observation is that about 50% of all jobs in Swedish manufacturing are potentially offshorable and only a small fraction of firms (approximately 5%) innovate.

#### 4. Empirical Strategy

We study the impact of offshoring destination on the share of workers with higher education and also on the skill premium, which is measured as the ratio of average wages of workers with a university education relative to workers with lower education. Both variables, *human capital* and *skill premium*, are censored at 0, but only *human capital* is censored at 1 as *skill premium* has values above 1. Given the cen-

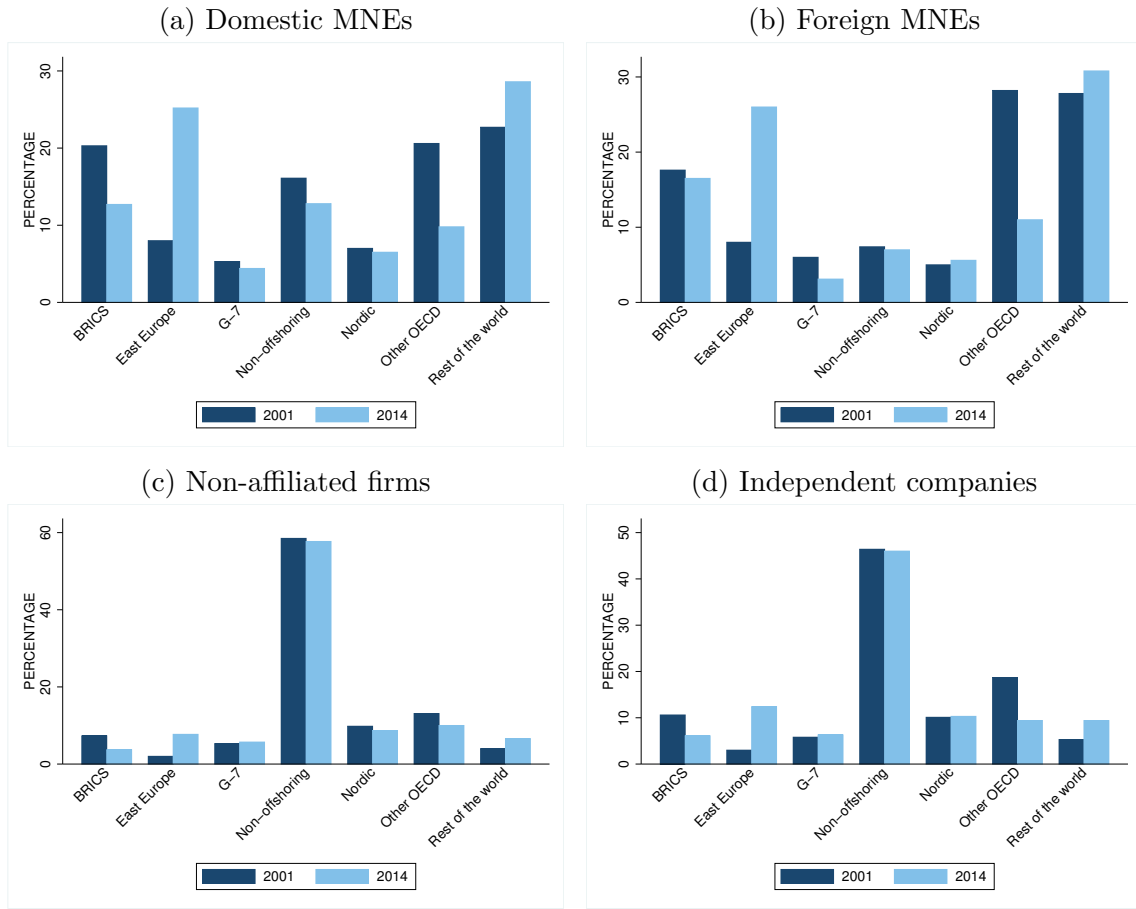


Figure 2: Offshoring Patterns by Destination and Ownership

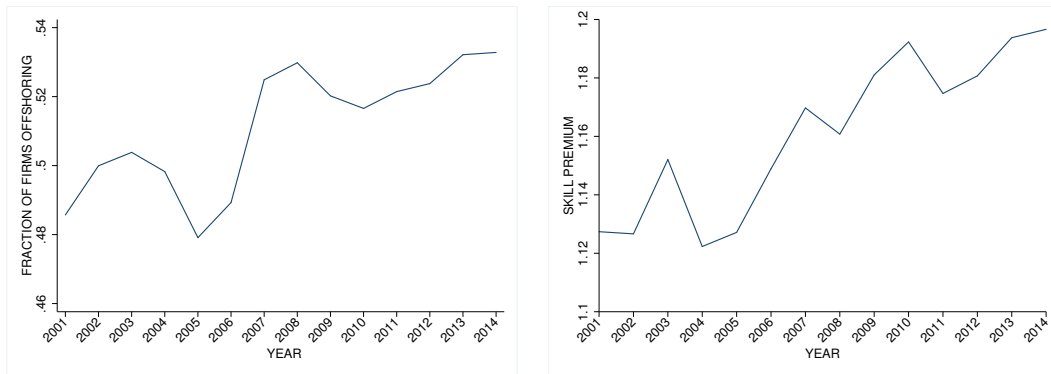


Figure 3: Offshoring and the skill premium in Sweden

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

sored nature of the dependent variables, both models,  $y = \{human\ capital, skill\ premium\}$ ,

are estimated as random effects Tobit models:

$$y_{it}^* = f(\text{offshoring destination}_{it}, \text{potential offshorability}_{it}, \text{workers' ability}_{it}, \text{automation potential}_{it}, \text{controls}_{it}, \mu_i, \lambda_t) + u_{it} \quad (1)$$

where

$$y_{it} = y_{it}^* \quad \text{if} \quad y_{it}^* > 0 \quad \text{and} \quad y_{it} = 0 \quad \text{otherwise.}$$

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

$$Pr(\text{patent}_{it} = 1) = f(\text{offshoring destination}_{it}, \text{potential offshorability}_{it}, \text{workers' ability}_{it}, \text{automation potential}_{it}, \text{controls}_{it}, \mu_i, \lambda_t) \quad (2)$$

where  $\mu_i$  is a firm-specific error term and  $\lambda_t$  is a year effect. This model is estimated as a random effects probit model.

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

$$\log \text{TFP}_{it} = f(\log \text{TFP}_{i,t-1}, \log \text{offshoring}_{it}, \text{potential offshorability}_{it}, \text{automation potential}_{it}, \text{workers' ability}_{it}, \text{controls}_{it}, \mu_i, \lambda_t) \quad (3)$$

To estimate this dynamic panel model specification, we employ the first-difference GMM estimator developed by [Arellano and Bond \(1991\)](#). This framework is convenient because it is relatively easy to allow for endogeneity of offshoring, which is instrumented with both its own lagged level values and external instruments together with other covariates.

## 5. Results

In this section, we present summary statistics and estimates for the models specified in equations (1)-(3). 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. Only five percent of the firms are defined as innovative according to the patent application statistics. 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, the firms have 7% skilled employees, and the mean skill premium is 0.75.

Our main offshoring measure is reported for all six destinations in the study. The most prevalent destinations are the G7 countries and other OECD countries when offshoring is normalized by sales. We estimate a Mincer residual for each employee, assuming 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, and the Osborne–Frey index suggests that 60% of the jobs in Swedish manufacturing can potentially be replaced by machines or robots. We denote this measure as *Automation potential*, assuming that a high value of this index reflects unexploited efficiency potential.

### 5.1. Labor Market Outcomes

Tables 3 and 4 report results in four columns. The first column shows estimates for all firms, not differentiating between offshoring destination. Columns (2)-(4) distinguish between offshoring destination and report results for all firms, firms classified as high-technology (HT) and medium-high technology (MHT), and medium-low technology (MLT) and low technology (LT) firms, respectively.

In Table 3 we test hypothesis H1: whether offshoring influences employment composition favoring skilled labor. There is a positive association between offshoring

Table 2: Summary statistics

| VARIABLE                        | OBS.   | MEAN  | SD    | 50 <sup>th</sup> PERCENTILE | MIN   | MAX   |
|---------------------------------|--------|-------|-------|-----------------------------|-------|-------|
| Innovation                      | 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 G7                | 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: Innovation is a indicator of patent application 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 fully-saturated Mincer residual. Potential offshorability and automation potential are the computed Blinder and Frey–Osborne indexes, respectively.

and skill-biased employment composition for all firms. Column (2) presents estimates for all firms when distinguishing between offshoring destination, and shows a positive and significant association for the G7, BRICS and Eastern Europe. Splitting the sample in two groups based on technology intensity, column (3) reports similar results for HT and MHT as for the entire sample, with the exception that the estimate for *Rest of the world* is positive and significant. The difference between columns (4) and (2) is that the estimate for *other OECD countries* is positive and significant in the former but not in the latter, i.e. only for LMT and LT firms.

Regarding the other covariates, all four columns are reporting that the higher is workers' ability, as measured by the Mincer residual, the less prone firms are to increase their fraction of university-educated employees. We also see that an increased fraction of employees working with routine tasks are candidates for being replaced by automation. This fraction is associated with a decreased ratio of skilled versus non-skilled employees. Larger firms, firms outside metro areas and high technology firms are likely to employ relatively more skilled employees than other firms.

Table 4 tests hypothesis H2 and shows the results for the skill premium, mea-



Table 3: Occupational structures, average marginal effects

|                                | (1)<br>All firms       | (2)<br>All firms       | (3)<br>HT and MHT      | (4)<br>LHT and LT      |
|--------------------------------|------------------------|------------------------|------------------------|------------------------|
| <b>OFFSHORING DESTINATION:</b> |                        |                        |                        |                        |
| All regions                    | 0.0104***<br>[0.0021]  |                        |                        |                        |
| Nordics                        |                        | 0.0028<br>[0.0050]     | 0.0113<br>[0.0094]     | 0.0104<br>[0.0064]     |
| G-7                            |                        | 0.0133***<br>[0.0028]  | 0.0205***<br>[0.0043]  | 0.0177***<br>[0.0038]  |
| Other OECD                     |                        | -0.0028<br>[0.0038]    | -0.0021<br>[0.0062]    | 0.0143***<br>[0.0049]  |
| BRICS                          |                        | 0.0233***<br>[0.0066]  | 0.0422***<br>[0.0104]  | 0.0187**<br>[0.0091]   |
| Eastern Euripe                 |                        | 0.0314***<br>[0.0114]  | 0.0423**<br>[0.0165]   | 0.0299*<br>[0.0175]    |
| Rest of the world              |                        | 0.0345<br>[0.0294]     | 0.1101**<br>[0.0450]   | 0.0477<br>[0.0392]     |
| <b>KEY CONTROLS:</b>           |                        |                        |                        |                        |
| Potential offshorability       | 0.0000***<br>[0.0000]  | 0.0000***<br>[0.0000]  | 0.0001***<br>[0.0000]  | 0.0000*<br>[0.0000]    |
| Workers' ability               | -0.0219***<br>[0.0010] | -0.0218***<br>[0.0010] | -0.0201***<br>[0.0016] | -0.0208***<br>[0.0013] |
| Automation potential           | -0.0243***<br>[0.0012] | -0.0243***<br>[0.0012] | -0.0280***<br>[0.0018] | -0.0231***<br>[0.0015] |
| <b>FIRM SIZE:</b>              |                        |                        |                        |                        |
| 30-49 employees                | 0.0032***<br>[0.0004]  | 0.0032***<br>[0.0004]  | 0.0033***<br>[0.0006]  | 0.0033***<br>[0.0005]  |
| 50-99 employees                | 0.0055***<br>[0.0006]  | 0.0055***<br>[0.0006]  | 0.0072***<br>[0.0010]  | 0.0060***<br>[0.0008]  |
| ≥ 100 employees                | 0.0073***<br>[0.0009]  | 0.0072***<br>[0.0009]  | 0.0095***<br>[0.0013]  | 0.0081***<br>[0.0011]  |
| <b>FIRM LOCATION:</b>          |                        |                        |                        |                        |
| Large cities                   | 0.0063***<br>[0.0015]  | 0.0062***<br>[0.0015]  | 0.0070***<br>[0.0019]  | 0.0059***<br>[0.0018]  |
| Rest of Sweden                 | 0.0169***<br>[0.0014]  | 0.0169***<br>[0.0014]  | 0.0187***<br>[0.0019]  | 0.0166***<br>[0.0018]  |
| <b>TECHNOLOGY GROUP:</b>       |                        |                        |                        |                        |
| MHT                            | -0.0025***<br>[0.0006] | -0.0026***<br>[0.0006] | -0.0139***<br>[0.0015] |                        |
| MLT                            | -0.0049***<br>[0.0006] | -0.0049***<br>[0.0006] |                        |                        |
| LT                             | -0.0051***<br>[0.0006] | -0.0051***<br>[0.0006] |                        | 0.0015**<br>[0.0007]   |
| Observations                   | 72,761                 | 72,761                 | 31,779                 | 40,982                 |

Standard errors in brackets. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

TABLE NOTES: Estimation is using panel-data random-effects tobit models. Dependent variable is a measure of human capital, defined as the share of university-educated workers to total employment, censored between 0 and 1. Firms with 10-29 employees, foreign MNEs, high-tech firms and firms located in Metropolitan areas are the reference groups. The measure for potential offshorability is the firm-specific 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. All regressions include ownership, firm and time fixed effects.

sured as the ratio of average wages of university-educated to non-university educated workers. All four columns report a highly significant and positive relationship between offshoring and the skill premium. The only exception is less technology intensive firms offshoring to *rest of the world*, which has a positive but not statistically significant estimate. We conclude that the hypothesis is supported by the estimates.

### 5.2. Innovation and technical change

Table 5 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. Hypothesis H3 predicts that this should be manifested through increased innovation capabilities. The hypothesis is confirmed for offshoring to low wage destinations, and partly for offshoring to *other OECD countries* (MTL and LT).

Our final analysis considers total factor productivity which can be considered as a broad measure of technical change, reflecting, amongst other things, innovation capabilities. The prior literature has mainly reported a positive relationship between offshoring and TFP and this is what we test in hypothesis H4. However, what distinguishes our analysis from the existing literature is that we observe mainly small firms over a lengthy period.

Table 6 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 two first 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 biased in a dynamic setting. Columns (3) and (4) presents 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 off-

Table 4: Skill premia, average marginal effects

|                                | (1)<br>All firms       | (2)<br>All firms       | (3)<br>HT and MHT      | (4)<br>LHT and LT      |
|--------------------------------|------------------------|------------------------|------------------------|------------------------|
| <b>OFFSHORING DESTINATION:</b> |                        |                        |                        |                        |
| All regions                    | 0.3185***<br>[0.0260]  |                        |                        |                        |
| Nordics                        |                        | 0.2818***<br>[0.0639]  | 0.4287***<br>[0.1127]  | 0.3488***<br>[0.0820]  |
| G-7                            |                        | 0.2945***<br>[0.0343]  | 0.2791***<br>[0.0516]  | 0.3936***<br>[0.0465]  |
| Other OECD                     |                        | 0.1634***<br>[0.0474]  | 0.2458***<br>[0.0768]  | 0.2647***<br>[0.0621]  |
| BRICS                          |                        | 0.3566***<br>[0.0838]  | 0.6011***<br>[0.1289]  | 0.2952**<br>[0.1177]   |
| Eastern Europe                 |                        | 0.4127***<br>[0.1470]  | 0.7950***<br>[0.2099]  | 0.5956***<br>[0.2250]  |
| Rest of the world              |                        | 0.5903<br>[0.3764]     | 2.1358***<br>[0.5729]  | 0.6036<br>[0.5073]     |
| <b>KEY CONTROLS:</b>           |                        |                        |                        |                        |
| Potential offshorability       | 0.0005***<br>[0.0001]  | 0.0004***<br>[0.0001]  | 0.0000<br>[0.0002]     | 0.0005***<br>[0.0002]  |
| Workers' ability               | -0.0415***<br>[0.0130] | -0.0405***<br>[0.0130] | -0.0010<br>[0.0205]    | -0.0607***<br>[0.0166] |
| Automation potential           | -0.2313***<br>[0.0148] | -0.2316***<br>[0.0148] | -0.2283***<br>[0.0226] | -0.2367***<br>[0.0193] |
| <b>FIRM SIZE:</b>              |                        |                        |                        |                        |
| 30-49 employees                | 0.1807***<br>[0.0049]  | 0.1804***<br>[0.0050]  | 0.1770***<br>[0.0073]  | 0.1964***<br>[0.0066]  |
| 50-99 employees                | 0.3679***<br>[0.0086]  | 0.3675***<br>[0.0086]  | 0.3716***<br>[0.0125]  | 0.3985***<br>[0.0116]  |
| ≥ 100 employees                | 0.5028***<br>[0.0125]  | 0.5013***<br>[0.0125]  | 0.5148***<br>[0.0180]  | 0.5406***<br>[0.0168]  |
| <b>FIRM LOCATION:</b>          |                        |                        |                        |                        |
| Large cities                   | 0.0385***<br>[0.0125]  | 0.0379***<br>[0.0125]  | 0.0504***<br>[0.0164]  | 0.0330**<br>[0.0153]   |
| Rest of Sweden                 | 0.0923***<br>[0.0121]  | 0.0916***<br>[0.0121]  | 0.0947***<br>[0.0161]  | 0.0692***<br>[0.0148]  |
| <b>TECHNOLOGY GROUP:</b>       |                        |                        |                        |                        |
| MHT                            | -0.0501***<br>[0.0082] | -0.0529***<br>[0.0082] | -0.1053***<br>[0.0157] |                        |
| MLT                            | 0.0036<br>[0.0078]     | 0.0023<br>[0.0078]     |                        |                        |
| LT                             | -0.0297***<br>[0.0081] | -0.0303***<br>[0.0081] |                        | 0.0057<br>[0.0081]     |
| Observations                   | 72,758                 | 72,758                 | 31,777                 | 40,981                 |

Standard errors in brackets. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

TABLE NOTES: Estimation is by panel-data, random-effects tobit models. Dependent variable is the skill premium, defined as the wage ratio of university-educated to non-university educated workers. Firms with 10-29 employees, foreign MNEs, high-tech firms and firms located in Metropolitan areas are the reference groups. 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. Measures of offshoring are winsorized to exclude the 1% extreme values of the upper tail of the distribution. All regressions include ownership, firm and time fixed effects.

Table 5: Innovation capabilities, average marginal effects

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

shoring 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 serial correlation in the differenced error terms. We therefore conclude that the estimates in Table 6 support hypothesis H4.

The overall picture is that there is a clear positive link between global value chains, as reflected by an increased reliance on offshoring and different measures of improved innovative capability. In this study, we can only interpret this relationship in terms of causality with regard to the effect on total factor productivity, but the results generally support the proposition that global value chains contribute to increasing firms’ capacity for innovation.

## **6. Conclusion**

Most prior studies on the impact of offshoring on firm innovation are based on large multinational enterprises and have a focus on research and development. The main issues are the effects of separation between R&D and production, and contracting out of innovation activities. Our study takes a different approach and examines how offshoring of production processes to six global destinations influence firms’ innovation capabilities. Guided by the literature, we consider these capabilities as a set of special assets including knowledge, technology, products, processes, experience, organization that facilitates and supports innovation. The paper uses the skill composition of the workforce, the skill premium, patenting and technical change as indicators on different aspects of a firm’s innovation capability.

We exploit Swedish manufacturing data for unique firms and individuals over the period 2001–2014. More than 60% of the about 7,500 firm have less than 30 employees, fewer than 20% are MNEs, and six out of ten are classified as low-technology or low-medium technology firms.

Table 6: Offshoring and total factor productivity (log TFP)

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

A major challenge in longitudinal analysis of offshoring at the firm level is to observe production processes contracted out, consistently for unique firms over time. In this paper, we take advantage of the opportunity offered by the United Nations Broad Economic Categories (BEC). Using this three-digit classification system we are able to group each transportable good entering each firm according to their main end use; capital goods, consumer goods and intermediate goods. The latter is applied as our proxy for offshoring intensity.

The empirical analysis tests four different hypotheses. The first two state that offshoring allows firms to increase the relative abundance of skilled labor, and predict a positive association between offshoring and the skill premium.

Our first results show that increased offshoring is associated with a change in the skill composition of the workforce, favoring skilled workers. This result is true for offshoring to both R&D-intensive regions (G7 countries), low-cost regions (Eastern Europe) and remote countries (BRICS). The link between offshoring and skills is even stronger when we estimate the skill premium. Offshoring to all regions, except the residual "rest of the world", is associated with increased returns for highly educated employees relative to other employees.

Our third analysis considers patent applications and tests the prediction that contracting out may allow firms to increase their resources for innovation. The hypothesis cannot be rejected regarding offshoring to destinations characterized by relatively low wages. For other destinations, we find no significant link between offshoring and patent applications with the exception of less technology-intensive firms. Here we find a positive and significant point estimate for offshoring to other OECD countries, except the G7 and Nordic neighbors.

Finally, we provide dynamic IV estimates for total factor productivity, using both internal and external instruments. The hypothesis we test: that firms are able to increase their TFP by moving inefficient in-house activities to efficient production abroad is supported by our empirical findings.

Our results show that the strategy of participating in global value chains increases the innovative capability of Swedish manufacturing firms. The results are robust to a wide set of controls and in line with both standard economic theory and recent models of directed technical change.

### *6.1. Managerial relevance*

What management outcome can be deduced from this study? Our data sample is dominated by small businesses. Many smaller companies that link to global value chains tend to trade primarily with neighboring countries, both for cost and knowledge reasons. But the results we present suggest that these companies can benefit from more distant global production, although the impact on innovation capability increases with firm size as well as technology intensity.

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## Appendix

Table 7: Variable definitions

| VARIABLE                 | MEASURE              | DEFINITION   |
|--------------------------|----------------------|--|
| Innovation               | dummy                | Dichotomous variable of patenting (patenting= 1; 0, otherwise)   |
| TFP                      | continuous           | Calculated according to <a href="#">Wooldridge (2009)</a> '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 <a href="#">Blinder and Krueger (2013)</a> 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 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.