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Offshoring, Total Factor Productivity and Skill-Biased Technological Change

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Abstract. The paper answers two questions simultaneously. What is the effect of offshoring on firms' total factor productivity? What is the effect of offshoring on skill-biased technological change? We estimate a model of firm production that allows for the effect of offshoring on both total factor productivity and relative skilled labor productivity, and for spillovers between the two. The model is fitted to Swedish firm-level data between 2001-2011. We find positive effects of offshoring intensity on total factor productivity, particularly of small domestic firms and large foreign-owned firms, and on skill-biased technological change in production of firms with low offshoring intensity. Initiating offshoring results in skill-biased technological change in non-production activities of large domestic firms. We show that evaluating the im-

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pact of offshoring in a unified framework has implications for the estimation results.

Keywords: Offshoring, total factor productivity, skill-biased technological change, relative skilled labor demand.

JEL classification: D24, F14, F16.

1 Introduction

Offshoring has intensified since the late 1980s. It has attracted considerable attention both in the media and in the academic literature, due to the observed or perceived effects of offshoring on wages and employment in both the origin and destination countries. In the media, offshoring has been blamed for the loss of jobs in developed countries and rising wage inequality, measured as the ratio of skilled to unskilled labor wages. In the academic literature, no consensus on the effects of offshoring has been reached so far (Gorg, 2011).

In this paper we will concern ourselves with a very specific definition of firm offshoring, namely, importing intermediate inputs from abroad as opposed to purchasing them from domestic suppliers (either affiliated or not). This measure is convenient as it is easily computed from firm-level production and trade data, and it has been widely used in the literature (Gorg et al., 2008; Kasahara and Rodrigue, 2008). The questions that we tackle are two-fold. First, we would like to empirically evaluate the dynamic effect of offshoring on firms' total factor productivity. Importing intermediate inputs from abroad may allow the transfer of foreign technological know-how, and necessitate or induce adoption of better managerial and production practices and an updating in production technologies, all of which results in higher total factor productivity. Higher total factor productivity will translate into higher production and employment levels, ceteris paribus. Second, we are interested in the dynamic effect of offshoring on skill-biased technological change and relative skilled labour demand. The managerial and technological innovations that take place at the firm due to offshoring may increase the productivity of skilled labor more than that of unskilled labor[1]. This skill-biased technological change implies an increase in relative skilled labour demand, which contributes to higher wage inequality.

Many papers have addressed either of these issues individually. Blalock and Veloso (2007), Gorg et al. (2008), Halpern et al. (2011), Kasahara and Rodrigue (2008), Yasar and Morrison Paul (2007), and Zhang (2014) show that importing intermediate inputs has a positive effect on firms' total factor productivity, using Indonesian, Irish, Hungarian, Chilean, Turkish, and Colombian micro data, respectively. Vogel and Wagner (2010) find no evidence for positive effects of importing on productivity in their data on German enterprises. Schor (2004), Amiti and Konings (2007) and Topalova and Khandelwal (2011) provide indirect evidence of the beneficial effect of foreign intermediate input use by evaluating the contribution of the reduction in import tariffs on intermediate inputs to firms' productivity in Brazil, Indonesia and India, respectively.

Biscourp and Kramarz (2007) find in the French firm-level data that there is a strong correlation between importing finished goods (but not intermediate inputs) and destruction of production jobs, and particularly destruction of unskilled production jobs in large firms. Andersson and Karpaty (2012) provide evidence of increasing

[1] Acemoglu et al. (2015) present a general equilibrium model of directed technical change, where both offshoring and innovation are endogenous, and offshoring impacts on the skill bias of technical change. Particularly, they show that at low levels of offshoring the technical change is likely to be skill-biased. However, further offshoring will induce unskilled-biased technical change, as the wage gap between the developed and developing countries narrows. Our work is not a test of this model, especially since we are interested in the effect of offshoring within the firm on the firm's technological change, ceteris paribus, rather than in the aggregate relationship over time between offshoring and innovation.

relative skilled labor demand due to services offshoring, but not goods offshoring, in Swedish firms. One way to explain the link between offshoring and relative skilled labor demand is by relying on the Feenstra and Hanson (1996) model, where unskilled labor intensive tasks previously produced by the firm are offshored, which leads to a reduction in unskilled labor demand relative to skilled labor demand. Since we cannot claim that the intermediate inputs that firms import used to be produced by the firm itself (in our data we only observe the purchases by firms of intermediate inputs from other suppliers, either domestic or foreign), we rely on the more indirect mechanism of skill-biased technological change as a result of importing, and therefore a shift in relative skilled labor demand. Kasahara et al. (2013) estimate a model of importing and skill-biased technological change, using Indonesian plant-level data, and show that offshoring substantially increased the relative demand for educated production workers, but had little effect on the relative demand for educated non-production workers.

To the best of our knowledge, we are the first to consider the two questions outlined above in a single framework. This requires estimating a production function where both total factor productivity and relative skilled-labor productivity are firm-specific and time-varying. Our work is related to papers by Doraszelski and Jaumandreu (2014) and Zhang (2015), who also estimate production functions with multi-dimensional productivity. Doraszelski and Jaumandreu (2014) consider a model where both factor-neutral and labor-augmenting technological change is allowed. Zhang (2015) evaluates a model with capital-augmenting, labor-augmenting and material-augmenting productivity changes. Just like these authors, we rely on the first-order conditions from the firm's profit maximisation problem to identify the multiple dimensions of productivity change, and particularly to address Diamond's Impossibility Theorem. Diamond et al. (1978) prove that under some standard assumptions the elasticity of substitution between inputs and biased technological change cannot be identified simultaneously. Introducing additional structure in the form of the first order conditions for the choice of inputs allows one to overcome this issue.

Our work is different from Doraszelski and Jaumandreu (2014) and Zhang (2015) in that we are interested in changes in total factor productivity and relative skilled labor productivity, and how offshoring affects these. Moreover, we allow for interaction between the two types of technological change. Changes in total factor productivity are assumed to feed into skill-biased technological change, and vice versa. An increase in total factor productivity may spur further innovation, which may affect the productivities of skilled and unskilled labor unevenly. Conversely, a relative increase in skilled labor productivity may imply higher productivity of engineers and researchers within the firm, which in turn leads to future total factor productivity growth. If instead factor-neutral and skilled-labor augmenting innovation are competing for the firm's limited resources, there may be a negative relationship between total factor productivity and relative skilled labor productivity changes.

We consider a value added production function with capital, production labor and non-production labor as inputs. Total factor productivity, as well as relative skilled labor productivity in production and relative skilled labor productivity in non-production are firm-specific and time-varying. The dynamics of any of these productivity terms depends on past offshoring and the other productivity dimensions, among other things. This model is fit to Swedish firm-level data between 2001-2011. We find significant positive effects of offshoring intensity on total factor productivity, particularly, for domestic firms with low value added and foreign-owned firms with high value added/high offshoring intensity. An increase in offshoring intensity leads to skill-biased technological change in production activities of both domestic and foreign-owned firms with low offshoring intensity. A switch from not offshoring to offshoring results in skill-biased technological change in non-production activities of domestic firms with high value added/high employment size/high offshoring intensity.

Moreover, we find statistically significant spillovers between total factor productivity and relative skilled labor productivity in production and non-production activities.

There is mostly a negative relationship between skill-biased technological change (in either production or non-production) and factor-neutral technological change, while increases in relative skilled labor productivity in production and non-production activities are positively associated.

This emphasises the importance of a unified framework to estimate the multiple dimensions of technological change, and evaluate the impact of offshoring on these. We consider an alternative model where TFP is the sole focus of estimation. This model delivers no significant effects of offshoring on productivity, unlike the baseline model, and this result is confirmed by bootstrapping. Thus, introducing a more general framework can produce dramatically different conclusions, which has implications both for the academic debate on the effects of offshoring and for policy recommendations.

The rest of the paper is organised as follows. Section 2 lays out the theoretical model, Section 3 discusses the data, and Section 4 presents the results. Section 5 presents the alternative model and the corresponding estimation results. Section 6 concludes.

2 Theoretical Framework

We carry out estimation for each industry separately. We extend the theoretical framework of Kasahara et al. (2013), who consider the following Cobb-Douglas production function with embedded CES aggregator functions:

$$Y_{it} = Q_{it} e^{u_{it}},$$

$$Q_{it} \equiv L_{p,it}^{\alpha_p} L_{n,it}^{\alpha_n} K_{it}^{\alpha_k} e^{\omega_{it}},$$

where i indexes firms in a given industry, and t indexes time (years in our case), Y is the value added, that is, gross output net of intermediate components and raw materials, L_p, L_n, K are inputs - production labor, non-production labor, and capital, respectively, $e^{\omega_{it}}$ is unobserved total factor productivity (TFP), u_{it} is an error term, representing shocks to production that are not observed by firms before making their input decisions at t. We deal with a value added production function, which requires an implicit assumption that the intermediate inputs are a fixed proportion of the gross physical output ($M = mY$, where M is the intermediate inputs quantity, Y is gross physical output, and m is a positive real number).

Moreover, production and non-production labor are composites of skilled and unskilled labor units:

$$L_{p,it} = ((A_{p,it}L^s_{p,it})^{\frac{\sigma_p-1}{\sigma_p}} + (L^u_{p,it})^{\frac{\sigma_p-1}{\sigma_p}})^{\frac{\sigma_p}{\sigma_p-1}},$$

$$L_{n,it} = ((A_{n,it}L^s_{n,it})^{\frac{\sigma_n-1}{\sigma_n}} + (L^u_{n,it})^{\frac{\sigma_n-1}{\sigma_n}})^{\frac{\sigma_n}{\sigma_n-1}},$$

where L^s_p and L^u_p are the number of units of skilled and unskilled labor employed in production, respectively, and L^s_n and L^u_n are the number of units of skilled and unskilled labor employed in non-production activities, respectively. The constants $A_{p,it} \in R^+$ and $A_{n,it} \in R^+$ are the relative skilled labor productivity terms in production and non-production activities of firm i in year t, respectively, and an increase in $A_p(A_n)$ reflects skill-biased technological change in production (non-production) activities.[2]

[2]Note that the model is isomorphic to the following model: $Y_{it} = Q_{it}e^{u_{it}}, Q_{it} = \tilde{L}^{\alpha_p}_{p,it}\tilde{L}^{\alpha_n}_{n,it}K^{\alpha_k}_{it}e^{\tilde{\omega}_{it}}$,

$$\tilde{L}_{p,it} = ((B^s_{p,it}L^s_{p,it})^{\frac{\sigma_p-1}{\sigma_p}} + (B^u_{p,it}L^u_{p,it})^{\frac{\sigma_p-1}{\sigma_p}})^{\frac{\sigma_p}{\sigma_p-1}}, \qquad \tilde{L}_{n,it} = ((B^s_{n,it}L^s_{n,it})^{\frac{\sigma_n-1}{\sigma_n}} + (B^u_{n,it}L^u_{n,it})^{\frac{\sigma_n-1}{\sigma_n}})^{\frac{\sigma_n}{\sigma_n-1}},$$

$B^s_{p,it}, B^s_{n,it}, B^u_{p,it}, B^u_{n,it} \in R^+$. Transform the above two equations:

$$\tilde{L}_{p,it} = B^u_{p,it}((A_{p,it}L^s_{p,it})^{\frac{\sigma_p-1}{\sigma_p}} + (L^u_{p,it})^{\frac{\sigma_p-1}{\sigma_p}})^{\frac{\sigma_p}{\sigma_p-1}}, \qquad \tilde{L}_{n,it} = B^u_{n,it}((A_{n,it}L^s_{n,it})^{\frac{\sigma_n-1}{\sigma_n}} + (L^u_{n,it})^{\frac{\sigma_n-1}{\sigma_n}})^{\frac{\sigma_n}{\sigma_n-1}},$$

where $A_{p,it} \equiv \frac{B^s_{p,it}}{B^u_{p,it}}$, $A_{n,it} \equiv \frac{B^s_{n,it}}{B^u_{n,it}}$ are the relative skilled labor productivity terms. Then

$$Q_{it} = L^{\alpha_p}_{p,it}L^{\alpha_n}_{n,it}K^{\alpha_k}_{it}e^{\omega_{it}},$$

where $L_{p,it} \equiv \frac{\tilde{L}_{p,it}}{B^u_{p,it}}$, $L_{n,it} \equiv \frac{\tilde{L}_{n,it}}{B^u_{n,it}}$ and $e^{\omega_{it}} \equiv e^{\tilde{\omega}_{it}}(B^u_{p,it})^{\alpha_p}(B^u_{n,it})^{\alpha_n}$. We cannot identify separately $\tilde{\omega}_{it}, B^u_{p,it}$ or $B^u_{n,it}$, and can only identify ω_{it}, and $A_{p,it}, A_{n,it}$. Increases in $A_{p,it}, A_{n,it}$ signal increases in relative skilled labor productivity terms $\frac{B^s_{p,it}}{B^u_{p,it}}$, $\frac{B^s_{n,it}}{B^u_{n,it}}$, that is, skill-biased technological change.

The first-order conditions of the firm's profit maximisation problem with respect to $L^s_{j,it}, L^u_{j,it}, j = p, n$, are given by

$$\frac{W^u_t L^u_{j,it}}{Q_{it}} = \alpha_j \frac{(L^u_{j,it})^{\frac{\sigma_j - 1}{\sigma_j}}}{(A_{j,it} L^s_{j,it})^{\frac{\sigma_j - 1}{\sigma_j}} + (L^u_{j,it})^{\frac{\sigma_j - 1}{\sigma_j}}},$$

$$\frac{W^s_t L^s_{j,it}}{Q_{it}} = \alpha_j \frac{(A_{j,it} L^s_{j,it})^{\frac{\sigma_j - 1}{\sigma_j}}}{(A_{j,it} L^s_{j,it})^{\frac{\sigma_j - 1}{\sigma_j}} + (L^u_{j,it})^{\frac{\sigma_j - 1}{\sigma_j}}},$$

which gives us

$$(\frac{L^u_{j,it}}{L^s_{j,it}})^{\frac{1}{\sigma_j}} A_{j,it}^{\frac{\sigma_j - 1}{\sigma_j}} = \frac{W^s_t}{W^u_t}, \quad \text{for} \quad j = p, n, \tag{1}$$

where W^s_t and W^u_t are the wages of skilled and unskilled labor in year t, respectively.

Substituting (1) into the expressions for $L_{p,it}$ and $L_{n,it}$, we obtain

$$L_{j,it} = X_{j,it}^{-\frac{\sigma_j}{\sigma_j - 1}} L^u_{j,it}, \quad \text{where} \quad X_{j,it} \equiv \frac{W^u_t L^u_{j,it}}{W^s_t L^s_{j,it} + W^u_t L^u_{j,it}}, \quad \text{for} \quad j = p, n.$$

Substituting these equations into the production function and taking the logarithm results in

$$y_{it} = \alpha_k k_{it} + \alpha_p l^u_{p,it} + \beta_p x_{p,it} + \alpha_n l^u_{n,it} + \beta_n x_{n,it} + \omega_{it} + u_{it}, \tag{2}$$

where the lower case letters denote the logarithms of the upper case variables (e.g. $y_{it} \equiv \ln Y_{it}$), and $\beta_j \equiv -\frac{\sigma_j \alpha_j}{\sigma_j - 1}$, for $j = p, n$.

Taking the logarithm of equation (1), we can also get

$$r_{j,it} = \sigma_j s_{j,t} - (\sigma_j - 1) \ln A_{j,it}, \tag{3}$$

where $r_{j,it} \equiv \ln(\frac{L^u_{j,it}}{L^s_{j,it}})$, and $s_{j,t} \equiv \ln \frac{W^s_t}{W^u_t}$.

We propose the following dynamics for the logged TFP term ω:

$$\begin{aligned} \omega_{it} = {} & \xi_t + \gamma_1 \omega_{i(t-1)} + \gamma_2 \omega^2_{i(t-1)} + \gamma_3 \omega^3_{i(t-1)} \\ & + \gamma_4 \ln off_{i(t-1)} + \gamma_5 \ln exp_{i(t-1)} + \gamma_6 \ln A_{p,i(t-1)} + \gamma_7 \ln A_{n,i(t-1)} + \nu_{it}, \end{aligned} \tag{4}$$

where ξ_t is an industry-specific total factor productivity shock, $\ln off_{it} \equiv \ln(1 + \frac{M^f_{it}}{M_{it}})$ is the logged offshoring intensity of firm i in year t, where M^f_{it} is the quantity of intermediate inputs imported from abroad, and M_{it} is the total quantity of intermediate inputs used in production, $\ln exp_{it} \equiv \ln(1 + \frac{E_{it}}{Y_{it}})$ is the logged exporting intensity of firm i in year t, where E_{it} is the total volume of exports and Y_{it} is gross output of the firm, and ν_{it} is a firm-specific zero-mean shock to ω in year t, which is unforeseen before year t and is independent of ξ_t.

We also propose the following dynamics for the logged skill-biased technological terms $A_{p,it}$ and $A_{n,it}$:

$$\begin{aligned}\ln A_{p,it} = \zeta_{p,t} + \theta_{p,1} \ln A_{p,i(t-1)} + \theta_{p,2}(\ln A_{p,i(t-1)})^2 + \theta_{p,3}(\ln A_{p,i(t-1)})^3 \\ + \theta_{p,4} \ln off_{i(t-1)} + \theta_{p,5} \ln exp_{i(t-1)} + \theta_{p,6}\omega_{i(t-1)} + \theta_{p,7} \ln A_{n,i(t-1)} + \eta_{p,it},\end{aligned} \tag{5}$$

$$\begin{aligned}\ln A_{n,it} = \zeta_{n,t} + \theta_{n,1} \ln A_{n,i(t-1)} + \theta_{n,2}(\ln A_{n,i(t-1)})^2 + \theta_{n,3}(\ln A_{n,i(t-1)})^3 \\ + \theta_{n,4} \ln off_{i(t-1)} + \theta_{n,5} \ln exp_{i(t-1)} + \theta_{n,6}\omega_{i(t-1)} + \theta_{n,7} \ln A_{p,i(t-1)} + \eta_{n,it},\end{aligned} \tag{6}$$

where $\zeta_{p,t}$ and $\zeta_{n,t}$ are industry-specific relative skilled labor productivity shocks, $\eta_{p,it}$ and $\eta_{n,it}$ are firm-specific zero-mean shocks to $\ln A_{p,it}$ and $\ln A_{n,it}$, respectively, which are unforeseen before year t and are independent of $\zeta_{p,t}$ and $\zeta_{n,t}$, respectively.

We assume therefore that changes in total factor productivity can affect future direction of skill-biased technological progress in production and non-production activities, and that skill-biased technological progress in production and non-production activities can affect future values of total factor productivity of the firm.

This dynamic interaction necessitates joint estimation of ω and $\ln A_p$, $\ln A_n$. We do this by jointly fitting equations (2) and (3), as well as (4) and (5), (6) to the data.

We incorporate the ACF (Ackerberg et al., 2006) critique of the Levinsohn and Petrin (2003) and Olley and Pakes (1996) estimation approaches, and estimate all production coefficients in the second stage of our estimation.

The first stage consists of relying on the equation for the optimal choice of intermediate inputs (in logs)

$$m_{it} = m_t(\omega_{it}, k_{it}),$$

to invert:

$$\omega_{it} \equiv \psi_t(m_{it}, k_{it}),$$

assuming monotonicity in the function $m_t(.)$. Inserting this into the expression for value added:

$$y_{it} = \alpha_k k_{it} + \alpha_p l^u_{p,it} + \beta_p x_{p,it} + \alpha_n l^u_{n,it} + \beta_n x_{n,it} + \psi_t(m_{it}, k_{it}) + u_{it}.$$

It is evident from the above that the coefficient α_k is not identified, since k_{it} appears in $\psi(m_{it}, k_{it})$, and the coefficients α_p, α_n are not identified, since the optimal choice of $l^u_{p,it}$ and $l^u_{n,it}$ likely depends on $\omega_{it} \equiv \psi_t(m_{it}, k_{it})$.

We can however estimate the residual u_{it} by fitting the regression equation

$$y_{it} \equiv \alpha_p l^u_{p,it} + \beta_p x_{p,it} + \alpha_n l^u_{n,it} + \beta_n x_{n,it} + \Psi(m_{it}, k_{it}) + u_{it},$$

where $\Psi(m_{it}, k_{it})$ is a polynomial in capital and intermediate inputs with time-specific coefficients[3]. Using the obtained estimates, we can purge y_{it} of the error term u_{it}:

$$\hat{y}_{it} \equiv y_{it} - \hat{u}_{it}.$$

In the second stage we apply GMM to estimate $\alpha_k, \alpha_p, \alpha_n, \sigma_p, \sigma_n$. For given values of $\alpha_k, \alpha_p, \alpha_n, \sigma_p, \sigma_n$, one can calculate $\beta_j \equiv -\frac{\sigma_j \alpha_j}{\sigma_j - 1}$, for $j = p, n$. Next, calculate ω_{it} from

$$\omega_{it} = \hat{y}_{it} - \alpha_k k_{it} - \alpha_p l^u_{p,it} - \beta_p x_{p,it} - \alpha_n l^u_{n,it} - \beta_n x_{n,it},$$

[3]Denote by D_t year dummies,

$$\Psi(m_{it}, k_{it}) \equiv \sum_{t=1}^{T} b_{0t} D_t + \sum_{t=1}^{T} b_{1mt} D_t m_{it} + \sum_{t=1}^{T} b_{1kt} D_t k_{it} + \sum_{t=1}^{T} b_{2mkt} D_t k_{it} m_{it} + \sum_{t=1}^{T} b_{2mmt} D_t m_{it}^2 + \sum_{t=1}^{T} b_{2kkt} D_t k_{it}^2$$
$$+ \sum_{t=1}^{T} b_{3kkmt} D_t k_{it}^2 m_{it} + \sum_{t=1}^{T} b_{3kmmt} D_t k_{it} m_{it}^2 + \sum_{t=1}^{T} b_{3kkkt} D_t k_{it}^3 + \sum_{t=1}^{T} b_{3mmmt} D_t m_{it}^3.$$

and calculate $\ln A_{p,it}, \ln A_{n,it}$ from (3):

$$\ln A_{j,it} = \frac{\sigma_j}{\sigma_j - 1} s_{j,t} - \frac{1}{\sigma_j - 1} r_{j,it}, \quad j = p, n.$$

We would like to estimate the residual ν_{it} from regression (4). However, this equation is subject to a selection bias, since we only observe firms with high enough productivity to stay active. That is, a firm i produces in year t if and only if $\omega_{it} \geq \underline{\omega}_t(k_t)$, where $\underline{\omega}_t(k_t)$ is a threshold below which firms do not produce in year t, which depends on the capital stock of the firm in year t and industry-level demand and cost considerations (hence the subscript t). We rely on the Heckman correction (Heckman, 1979) to tackle this issue.

The selection equation is

$$\begin{aligned} S^*_{it} \equiv \omega_{it} - \underline{\omega}_t(k_t) &= \xi_t + \gamma_1 \omega_{i(t-1)} + \gamma_2 \omega^2_{i(t-1)} + \gamma_3 \omega^3_{i(t-1)} \\ &+ \gamma_4 \ln off_{i(t-1)} + \gamma_5 \ln exp_{i(t-1)} + \gamma_6 \ln A_{p,i(t-1)} + \gamma_7 \ln A_{n,i(t-1)} - \underline{\omega}_t(k_t) + \nu_{it}, \end{aligned} \tag{7}$$

$$S_{it} = \begin{cases} 1 & \text{if} \quad S^*_{it} > 0, \\ 0 & \text{if} \quad S^*_{it} \leq 0, \end{cases}$$

and the outcome equation is

$$\begin{aligned} \omega_{it} &= \xi_t + \gamma_1 \omega_{i(t-1)} + \gamma_2 \omega^2_{i(t-1)} + \gamma_3 \omega^3_{i(t-1)} \\ &+ \gamma_4 \ln off_{i(t-1)} + \gamma_5 \ln exp_{i(t-1)} + \gamma_6 \ln A_{p,i(t-1)} + \gamma_7 \ln A_{n,i(t-1)} + \nu_{it}, \quad \text{if} \quad S_{it} = 1. \end{aligned} \tag{8}$$

Since $\omega_{i(t-1)}$ can be expressed as

$$\omega_{i(t-1)} \equiv \psi_{t-1}(m_{i(t-1)}, k_{i(t-1)}),$$

and by assumption k_{it} is predetermined by $k_{i(t-1)}$ and investment in year t, $i_{i(t-1)}$, we formulate the following probit equation:

$$\begin{aligned} Prob(S_{it} = 1) &= \Phi(\sum_{t=1}^{T} \delta_t D_t + \delta_k k_{i(t-1)} + \delta_m m_{i(t-1)} + \delta_i i_{i(t-1)} + \delta_{kk} k^2_{i(t-1)} + \delta_{mm} m^2_{i(t-1)} \\ &+ \delta_{ii} i^2_{i(t-1)} + \delta_{mk} m_{i(t-1)} k_{i(t-1)} + \delta_{ik} i_{i(t-1)} k_{i(t-1)} + \delta_{off} \ln off_{i(t-1)} + \delta_{exp} \ln exp_{i(t-1)}) \\ &\equiv \Phi(X\delta), \end{aligned} \tag{9}$$

where D_t are year dummies, and Φ is the cumulative distribution function of the standard normal distribution. $X \equiv [D_1, ..., D_T, k_{i(t-1)}, m_{i(t-1)}, i_{i(t-1)}, k^2_{i(t-1)}, m^2_{i(t-1)}, i^2_{i(t-1)}, m_{i(t-1)}k_{i(t-1)}, i_{i(t-1)}k_{i(t-1)}, \ln off_{i(t-1)}, \ln exp_{i(t-1)}]$, and $\delta \equiv [\delta_1, ..., \delta_T, \delta_k, \delta_m, \delta_i, \delta_{kk}, \delta_{mm}, \delta_{ii}, \delta_{mk}, \delta_{ik}, \delta_{off}, \delta_{exp}]'$.

Once we fit equation (9), we can calculate the non-selection hazard ratio, or the inverse Mills ratio, for each observation point, as

$$nsh(X\hat{\delta}) = \frac{\phi(X\hat{\delta})}{\Phi(X\hat{\delta})},$$

where ϕ denotes the probability density function of the standard normal distribution. We then include the non-selection hazard ratio as an additional explanatory variable in the regression for ω:

$$\begin{aligned} \omega_{it} = \xi_t + \gamma_1\omega_{i(t-1)} + \gamma_2\omega^2_{i(t-1)} + \gamma_3\omega^3_{i(t-1)} + \gamma_4 \ln off_{i(t-1)} \\ + \gamma_5 \ln exp_{i(t-1)} + \gamma_6 \ln A_{p,i(t-1)} + \gamma_7 \ln A_{n,i(t-1)} + \gamma_8 nsh(X\hat{\delta}) + \nu_{it}. \end{aligned} \tag{10}$$

Estimate the residual ν_{it} by running regression (10) and estimate the residuals $\eta_{p,it}, \eta_{n,it}$ by running regressions (5), (6)[4].

Use the moments

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \sigma_p, \sigma_n)k_{it}] = 0,$$

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \sigma_p, \sigma_n)l^u_{p,i(t-1)}] = 0,$$

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \sigma_p, \sigma_n)x_{p,i(t-1)}] = 0,$$

[4]A measure of the logged skilled-to-unskilled wage ratio $s_t \equiv \ln \frac{W^s_t}{W^u_t}$ is necessary to run these regressions. We evaluate it as the logged skill premium obtained as the coefficient on the skilled-worker dummy from a Mincer regression

$$\ln w^k_t = c_{0t} + c_{1t}age_{kt} + c_{2t}age^2_{kt} + c_{3t}D^s_k + e_{kt},$$

where w^k_t is the wage of a worker k at time t, age_{kt} is his or her age, and $D^s_k = 1$ if the worker is highly-skilled and 0 otherwise. We use age as a proxy for experience, and run this regression with plant-fixed effects (the employee data is available at the plant level, and a firm may comprise several plants). The coefficient on the dummy D^s_k obtained by running this regression for each year is treated as the logged skill premium s_t in that year.

$$E[\nu_{it}(\alpha_k,\alpha_p,\alpha_n,\sigma_p,\sigma_n)l^u_{n,i(t-1)}]=0,$$

$$E[\nu_{it}(\alpha_k,\alpha_p,\alpha_n,\sigma_p,\sigma_n)x_{n,i(t-1)}]=0,$$

$$E[\eta_{p,it}(\alpha_k,\alpha_p,\alpha_n,\sigma_p,\sigma_n)r_{p,i(t-1)}]=0,$$

$$E[\eta_{n,it}(\alpha_k,\alpha_p,\alpha_n,\sigma_p,\sigma_n)r_{n,i(t-1)}]=0,$$

to identify the parameters $\alpha_k,\alpha_p,\alpha_n,\sigma_p,\sigma_n$. Since we have 7 moments to estimate 5 parameters, we conduct the test for over-identifying restrictions, which allows us to check whether the moment conditions match the data well or not.

Given estimates $\hat{\alpha}_k,\hat{\alpha}_p,\hat{\alpha}_n,\hat{\sigma}_p,\hat{\sigma}_n$, and $\hat{\beta}_p\equiv-\frac{\hat{\sigma}_p\hat{\alpha}_p}{\hat{\sigma}_p-1}$, $\hat{\beta}_n\equiv-\frac{\hat{\sigma}_n\hat{\alpha}_n}{\hat{\sigma}_n-1}$, the estimate of the logged total factor productivity ω is given by

$$\widehat{\omega_{it}}=\hat{y}_{it}-\hat{\alpha}_k k_{it}-\hat{\alpha}_p l^u_{p,it}-\hat{\beta}_p x_{p,it}-\hat{\alpha}_n l^u_{n,it}-\hat{\beta}_n x_{n,it},$$

and the estimates of the logged relative skilled labor productivity terms $\ln A_p$ and $\ln A_n$ are given by

$$\widehat{\ln A_{j,it}}=\frac{\hat{\sigma}_j}{\hat{\sigma}_j-1}s_t-\frac{1}{\hat{\sigma}_j-1}r_{j,it},\quad \text{for}\quad j=p,n.$$

We can then investigate the relationship between offshoring and firm productivity through the regressions

$$\begin{aligned}\widehat{\omega_{it}}&=\xi_t+\gamma_1\widehat{\omega_{i(t-1)}}+\gamma_2\widehat{\omega_{i(t-1)}}^2+\gamma_3\widehat{\omega_{i(t-1)}}^3+\gamma_4\ln off_{i(t-1)}\\&+\gamma_5\ln exp_{i(t-1)}+\gamma_6\widehat{\ln A_{p,i(t-1)}}+\gamma_7\widehat{\ln A_{n,i(t-1)}}+\gamma_8 nsh(X\hat{\delta})+\nu_{it},\end{aligned}\tag{11}$$

and

$$\begin{aligned}\widehat{\ln A_{p,it}}&=\zeta_{p,t}+\theta_{p,1}\widehat{\ln A_{p,i(t-1)}}+\theta_{p,2}(\widehat{\ln A_{p,i(t-1)}})^2+\theta_{p,3}(\widehat{\ln A_{p,i(t-1)}})^3\\&+\theta_{p,4}\ln off_{i(t-1)}+\theta_{p,5}\ln exp_{i(t-1)}+\theta_{p,6}\widehat{\omega_{i(t-1)}}+\theta_{p,7}\widehat{\ln A_{n,i(t-1)}}+\eta_{p,it},\end{aligned}\tag{12}$$

$$\begin{aligned}\widehat{\ln A_{n,it}}&=\zeta_{n,t}+\theta_{n,1}\widehat{\ln A_{n,i(t-1)}}+\theta_{n,2}(\widehat{\ln A_{n,i(t-1)}})^2+\theta_{n,3}(\widehat{\ln A_{n,i(t-1)}})^3\\&+\theta_{n,4}\ln off_{i(t-1)}+\theta_{n,5}\ln exp_{i(t-1)}+\theta_{n,6}\widehat{\omega_{i(t-1)}}+\theta_{n,7}\widehat{\ln A_{p,i(t-1)}}+\eta_{n,it}.\end{aligned}\tag{13}$$

Studying the effect of offshoring on the relative skilled labor productivity terms A_p and A_n directly gives us the effect of offshoring on relative skilled-labor demand from (3). Hence, if offshoring has a positive effect on $\ln A_p$ ($\ln A_n$), this implies that it has a positive effect on relative skilled-labor demand in production (non-production) activities, ceteris paribus.

3 Data and Descriptive Statistics

The data is obtained from the Swedish Survey of Manufacturers conducted by Statistics Sweden, the Swedish government's statistical agency. The survey covers all firms within manufacturing (2-digit NACE Rev.2 codes 10-32). We consider only firms with 10 or more employees, since the information provided for smaller firms is less reliable. We use data for the period 2001-2011, which is when the data on the occupation of workers employed by Swedish firms is available. The survey contains information on value-added, intermediate inputs, capital stock, investment and the number of employees at the firm level. We merge the firm-level data with the employee data, which provides information on their level of education and occupation. We define workers as 'high-skilled' if they have some university education, and 'low-skilled' otherwise.[5] Occupation is defined according to the Swedish Standard Classification of Occupations (SSYK). We define 'non-production' workers as workers with occupation codes 1-5 (managers, professionals, technicians, clerks and service workers). 'Production' workers are workers with occupation codes 6-9 (agricultural and fishery workers, craft and

[5] This definition is different from that of the papers that use data on developing countries, such as Kasahara et al. (2013), where workers with high-school education and above are considered as high-skilled. In Sweden, most workers, especially young ones, have at least some high school education. We therefore raise the bar for a worker to be called high-skilled in our dataset. Estimation was also carried out with the more standard definition of skill, but the results were much less reasonable. Particularly, the elasticities of substitution between skilled and unskilled labor were very high, as high as 6.4 for one industry, and above 2 for 10 out of 16 industries. The values with our definition exceed 2 in only 2 industries.

related trades workers, plant and machine operators and assemblers and elementary occupations).

We define intermediate inputs as inputs that are transformed by the firm. These include raw materials, but not energy inputs[6]. Our measure of intermediate inputs thus does not include goods that are sold onward without any modification. We define capital as tangible assets, which includes buildings, land and equipment. We calculate capital using the perpetual inventory method. Capital for year t equals the capital in year $t-1$ plus investment in year t, depreciating capital using Hulten and Wykoff (1981) depreciation rates for buildings (0.0361) and equipment (0.1179).

We deflate value-added, capital and intermediate inputs using data available from Statistics Sweden and follow the EUKLEMS methodology to construct the deflators[7]. The level of industry aggregation for the deflators appears in Table 19 in the Appendix. The deflators are available at the 2-digit industry level for most industries, but in some cases 2-digit industries are aggregated due to a lack of observations. We fit the production function for each industry individually, using the level of industry aggregation given in Table 19[8].

We merge the firm-level data with customs data on firms' exports and imports. Our measure of offshoring is offshoring intensity - the ratio of the quantity of imported intermediate inputs (in tons) to total intermediate inputs use by the firm (in thousands of SEK, deflated), or more precisely, $\ln off_{it} \equiv \ln(1 + \frac{M_{it}^f}{M_{it}})$[9]. We define imports as intermediate inputs if they correspond to 'Industrial supplies not elsewhere specified', using the Classification by Broad Economic Categories (BEC), revision 4. We match our trade data (Combined Nomenclature) to the BEC classification using a concordance provided by Eurostat. Logged exporting intensity is calculated as

[6]In the dataset, we observe a variable that incorporates both intermediate components and raw materials (excluding energy inputs), and we do not observe these separately.

[7]EUKLEMS does not report Swedish NACE rev.2 deflators for materials and capital.

[8]We omit 'Coke and refined petroleum products' (NACE rev.2 19) from the analysis due to a lack of observations.

[9]We introduce the 1 in the definition to allow observations with no offshoring to enter our dataset.

$\ln exp_{it} \equiv \ln(1 + \frac{E_{it}}{Y_{it}})$, where E_{it} is the total volume of exports (in thousands of SEK) and Y_{it} is gross output of the firm (in thousands of SEK).

The descriptive statistics in Table 1 indicate a large degree of heterogeneity among Swedish firms in terms of value-added, capital, employment, intermediate inputs and labor inputs, as well as offshoring and exporting intensities. Only 11% of firms in our dataset never offshore, and only around 2% of all firms in the dataset that we use for estimation never export (Table (2)).

In what follows, we will study how offshoring affects firms' productivity, differentiating firms according to ownership, size and offshoring intensity. Ownership is classified in Table (3). Less than 1% of all firms are state or municipality-owned, while 70% of firms are private Swedish-owned and almost 30% of firms are foreign-controlled. Firms will be classified as large or small depending on whether their value added/employment is larger or smaller than the median value added/employment in the industry. As can be seen from Table (4), there is large significant correlation between value added and employment of firms, and hence both are used to evaluate firm size for robustness check. There is no significant correlation between logged offshoring intensity and value added/employment. Logged offshoring intensity, value added and employment are all statistically significantly negatively correlated with the dummy for domestic firms, albeit the correlation coefficient values are quite small. We will run the main regressions for all firms first, and then by groups, interacting ownership with size (value added/employment) and offshoring intensity.

Table 1: Descriptive statistics

Variable	Obs.	Mean	Median	St. dev.	Min	Max
Value-added (SEK thousands)	28758	1.24e+08	2.29e+07	9.83e+08	28688.13	6.25e+10
Capital (SEK thousands)	28007	1.15e+08	1.61e+07	7.40e+08	31643.76	2.70e+10
Low-skilled production labour (employees)	28554	77.59256	27	239.8114	1	11152
High-skilled production labour (employees)	23626	7.593583	2	25.66185	1	981
Low-skilled non-production labour (employees)	28413	27.12829	9	106.2123	1	3593
High-skilled non-production labour (employees)	26838	31.17375	5	288.8302	1	13423
Intermediate inputs use (SEK thousands)	28586	1.86e+08	3.01e+07	1.18e+09	33.34439	4.94e+10
Logged offshoring intensity	19669	.02598	.0023005	.1133954	3.29e-10	7.017399
Logged exporting intensity	24621	.2563546	.2056756	.2297648	3.45e-09	2.105254

Based on the dataset used for estimation

Table 2: Distribution of firms according to offshoring/exporting

Category	Frequency	Percent	Category	Frequency	Percent
Never offshore	315	10.78	Never export	64	2.19
Offshore at least once	2,607	89.22	Export at least once	2,858	97.81
Total	2,922	100.00	Total	2,922	100.00

Based on the dataset used for estimation

Table 3: Distribution of firms according to ownership

Category	Frequency	Percent
State-owned	4	0.14
Municipality-owned	2	0.07
Private swedish-controlled, not part of conglomerate	404	13.83
Private swedish-controlled, part of conglomerate	1,644	56.26
Foreign-controlled	868	29.71
Total	2,922	100.00

Based on the dataset used for estimation

Table 4: Pairwise correlation between firm characteristics

	Offshoring	VA	Employment	Domestic
Offshoring	1.0000			
VA	0.0042	1.0000		
	(0.7569)			
Employment	0.0036	0.8627	1.0000	
	(0.7866)	(0.0000)		
Domestic	-0.0932	-0.1065	-0.1560	1.0000
	(0.0000)	(0.0000)	(0.0000)	

Based on the dataset used for estimation. P-values in parantheses.

Offshoring stands for logged offshoring intensity, VA - for value added,

Domestic - for dummy equal to 1 if the firm is a private domestically owned firm,

and 0 if the firm is a foreign-owned firm.

4 Results

In Table (5) we present the estimates of the parameters $\alpha_k, \alpha_p, \alpha_n, \sigma_p, \sigma_n$, and show their histograms in Figures (1)-(2). We estimate their standard errors by bootstrapping, with clustering by firms. All parameters are precisely estimated in all industries, and are statistically significantly greater than 0, at either 5 or 10% significance level. All sectors satisfy the test for over-identifying restrictions at either 5 or 10% confidence level.

In what follows we present the results of regressions (11), (12), and (13). The regressions are carried out pooling over all industries, with firm fixed effects and industry-year fixed effects. All standard errors are bootstrapped.

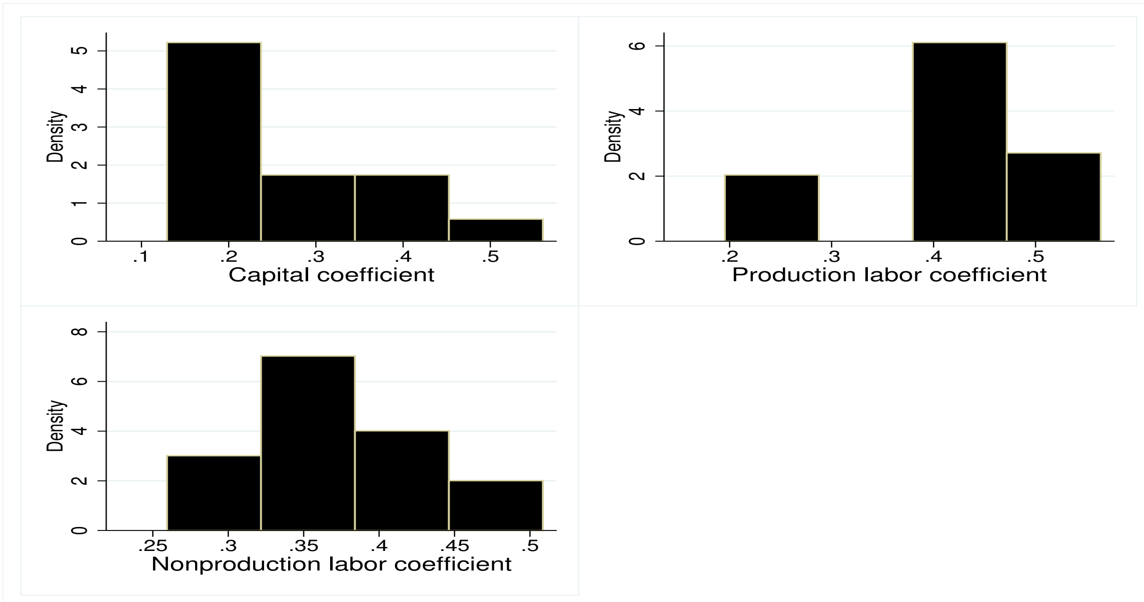

Figure 1: Histograms of the production function coefficients.

Figure 2: Histograms of the elasticities of substitution between skilled and unskilled labor.

Table 5: Estimated parameters.

Industry	α_k	α_p	α_n	σ_p	σ_n	p-value
Food products,	.56	.385	.28	1.326	1.254	0.93
beverages and tobacco	(.094)	(.088)	(.109)	(.289)	(.132)	
Textiles, wearing apparel,	.24	.426	.416	1.076	1.432	0.997
leather and related products	(.089)	(.074)	(.0815)	(.39)	(.734)	
Wood and products	.17	.448	.336	1.226	1.204	0.9
of wood and cork	(.059)	(.032)	(.036)	(.094)	(.1)	
Paper and	.384	.281	.3514	2.13	1.174	0.91
paper products	(.105)	(.083)	(.087)	(.733)	(.549)	
Printing and reproduction	.166	.564	.3177	1.13	1.196	0.96
of recorded media	(.086)	(.113)	(.081)	(.088)	(.078)	
Chemicals and	.449	.261	.454	1.044	1.71	0.97
chemical products	(.084)	(.093)	(.069)	(.265)	(.511)	
Rubber and	.221	.459	.337	1.345	2.286	0.96
plastics products	(.075)	(.079)	(.087	1.001)	(.782)	
Other non-metallic	.417	.195	.429	1.144	1.374	0.96
mineral products	(.091)	(.113)	(.113)	(.3182)	(.622)	
Basic metals	.293	.473	.259	1.02	1.319	1.00
	(.117)	(.189)	(.144)	(.364)	(.731)	
Fab. metal products, exc.	.176	.412	.365	1.142	1.361	0.98
machinery and equipment	(.037)	(.029)	(.028)	(.071)	(.048)	
Computer, electronic	.129	.395	.509	1.147	1.23	0.95
and optical equipment	(.0863)	(.095)	(.079)	(.132)	(.086)	
Electrical	.191	.468	.402	1.062	1.349	0.997
equipment	(.107)	(.11)	(.09)	(.239)	(.122)	
Machinery and	.159	.517	.433	1.08	1.33	0.96
equipment n.e.c.	(.093)	(.098)	(.1)	(.667)	(.18)	
Motor vehicles,	.21	.448	.361	1.043	1.2	0.99
trailers and semi-trailers	(.067)	(.127)	(.135)	(.206)	(.12)	
Other transport	.146	.423	.374	1.163	1.092	0.99
equipment	(.087)	(.113)	(.092)	(.15)	(.078)	
Furniture, other	.261	.489	.336	1.264	1.184	0.96
manufacturing	(.083)	(.082)	(.061)	(.192)	(.139)	

Bootstrapped standard errors in parantheses.

The p-value for the test for over-identifying restrictions in the last column.

4.1 The effect of offshoring on total factor productivity

In Table (6), we investigate the relationship between offshoring and firms' total factor productivity, by running regression (11) over all firms. Three specifications are considered. In specification (1) all observations are used, in specification (2) only observations with positive logged offshoring intensity are used (that is, where the quantity of imported intermediate inputs is larger than 0), and in specification (3) we regress total factor productivity on an offshoring dummy rather than logged offshoring intensity, where $offdum_{it}$ is equal to 1 if firm i is offshoring at time t, and 0 otherwise.

The results do not change much between specifications (1) and (2). We will base our discussion on specification (1). A 1% increase in offshoring intensity is associated with a 0.071% increase in TFP. The effect of offshoring is larger than that of exporting, where a 1% increase in exporting intensity results in a 0.056% increase in TFP. Past TFP has a large significant positive coefficient. We drop the second and third powers of $\omega_{i(t-1)}$ from the regression, as these terms are highly correlated with $\omega_{i(t-1)}$, and are not statistically significant. Past logged relative skilled labor productivity terms in production and non-production have statistically significant negative coefficients, though small in magnitude. A 1% increase in lagged relative skilled labor productivity in production (non-production) leads to a 0.001% (0.002%) decrease in TFP. The non-selection hazard ratio has a significant positive coefficient, which is consistent with the Heckman sample selection model, which predicts that the coefficient on the non-selection hazard ratio has the same sign as the correlation between the error terms in the outcome and selection equations. Since these equations in our case have the same error term (see equations (7) and (8)), this correlation is expected to be positive.

The lagged offshoring dummy in specification (3) does not have a statistically significant coefficient, which tells us that the positive effect of offshoring on TFP comes mostly from the variation in offshoring intensity for offshoring firms, rather than from switching from not offshoring to offshoring.

Table 6: Estimating equation (11) over all firms.

Dependent variable: ω_{it}	(1)	(2)	(3)
$\ln off_{i(t-1)}$	0.071**	0.073**	
	(0.031)	(0.034)	
$\ln exp_{i(t-1)}$	0.056***	0.043**	0.057***
	(0.018)	(0.022)	(0.018)
$\omega_{i(t-1)}$	0.364***	0.374***	0.364***
	(0.025)	(0.032)	(0.027)
$\ln A_{p,i(t-1)}$	-0.001***	-0.001**	-0.001**
	(0.000)	(0.001)	(0.000)
$\ln A_{n,i(t-1)}$	-0.002**	-0.002*	-0.002**
	(0.001)	(0.001)	(0.001)
nsh_{it}	0.169***	0.166**	0.166***
	(0.051)	(0.068)	(0.046)
$offdum_{i(t-1)}$			0.004
			(0.003)
Constant	0.007***	0.008***	0.006***
	(0.001)	(0.001)	(0.001)
Observations	18029	13146	18029
R^2	0.551	0.564	0.551

Specification (1) - all observations, specification (2) - only non-zero offshoring, specification (3) - offshoring dummy as explanatory variable.

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We tried including an R&D variable in the above regressions. The results are presented in Table (20) in the Appendix, where $rnd_{it} \equiv \ln(1 + \frac{R\&D_{it}}{employment_{it}})$ is logged R&D intensity, and $R\&D_{it}$ and $employment_{it}$ are R&D expenditures and employment size of firm i at time t, respectively. R&D data is available only for odd years in our dataset, and not for all firms, and hence we have much fewer observations in these regressions. Neither offshoring variables nor R&D intensity have significant coefficients, which indicates that the number of observations is important for detecting the effects of offshoring. We therefore do not include R&D intensity in the following regressions.

Next, we differentiate between firms by ownership and by size, according to value added in Table (7) and employment in Table (21) in the Appendix. We call a firm a low value added (low employment) firm if its highest value added (employment) is below the median of the firm-level highest value added (employment) within its industry.

As can be seen from Table (7), past offshoring intensity has a high significant positive effect on total factor productivity of low value added domestic firms, where a 1% increase in offshoring intensity results in an almost 0.5% increase in future TFP. This effect is much smaller, but also significant and positive, for high value added foreign-owned firms, at 0.063%. Past skill-biased technological changes in production and non-production activities have significant negative coefficients for high value added domestic firms, but not for the rest.

These results are replicated for most part when we measure size based on employment, rather than value added, in Table (21) in the Appendix. Past offshoring intensity has a significant positive coefficient of 0.061 for high employment foreign-owned firms, but has no significant effect for low employment domestic firms. There is now a negative significant coefficient on the past value of relative skilled labor productivity in production for low employment domestic firms.

Table 7: Estimating equation (11) by ownership and size (value added)

.

	Low value added, domestic	High value added, domestic	Low value added, foreign	High value added, foreign
$\ln off_{i(t-1)}$	0.492***	0.089	0.208	0.063**
	(0.179)	(0.085)	(0.229)	(0.028)
$\ln exp_{i(t-1)}$	0.045	0.083***	0.022	0.014
	(0.046)	(0.024)	(0.161)	(0.029)
$\omega_{i(t-1)}$	0.401***	0.316***	0.101	0.449***
	(0.040)	(0.030)	(0.109)	(0.045)
$\ln A_{p,i(t-1)}$	-0.001	-0.002***	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)
$\ln A_{n,i(t-1)}$	-0.002	-0.002**	0.007	-0.003
	(0.002)	(0.001)	(0.011)	(0.002)
nsh_{it}	0.257***	0.220***	-0.070	0.217*
	(0.085)	(0.070)	(0.256)	(0.118)
Constant	0.010***	0.005***	0.022**	0.007***
	(0.003)	(0.002)	(0.011)	(0.003)
Observations	3195	8796	440	5572
R^2	0.562	0.595	0.601	0.587

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Estimating equation (11) by ownership and offshoring intensity

.

	Low offshoring, domestic	High offshoring, domestic	Low offshoring, foreign	High offshoring, foreign
$\ln off_{i(t-1)}$	-3.065	0.118	-1.272	0.062**
	(2.534)	(0.084)	(3.825)	(0.031)
$\ln exp_{i(t-1)}$	0.161***	0.050**	0.086	-0.015
	(0.043)	(0.024)	(0.071)	(0.033)
$\omega_{i(t-1)}$	0.336***	0.345***	0.517***	0.304***
	(0.049)	(0.021)	(0.104)	(0.031)
$\ln A_{p,i(t-1)}$	-0.003**	-0.002***	0.003*	-0.001*
	(0.001)	(0.000)	(0.002)	(0.000)
$\ln A_{n,i(t-1)}$	-0.004**	0.000	-0.001	-0.004**
	(0.002)	(0.001)	(0.005)	(0.002)
nsh_{it}	0.178**	0.258***	-0.123	0.197*
	(0.078)	(0.069)	(0.282)	(0.118)
Constant	0.007***	0.005***	0.016**	0.007***
	(0.003)	(0.002)	(0.007)	(0.002)
Observations	4590	7401	1079	4933
R^2	0.507	0.635	0.565	0.590

Offshoring stands for offshoring intensity

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We are now interested in whether the effects of offshoring on TFP differ across firms with different offshoring intensity. A firm is called a low offshoring intensity firm if its highest offshoring intensity is below the median of the firm-level highest offshoring intensity within its industry.

From Table (8), offshoring intensity has a significant positive effect on TFP for high offshoring intensity foreign-owned firms, where a 1% increase in offshoring intensity translates into a 0.062% increase in TFP. Past skill-biased technological changes in production and non-production activities have significant negative coefficients in most instances, and only for low offshoring intensity foreign-owned firms does skill-biased technological change in production have a significant positive coefficient. The latter indicates possible positive spillovers between skill-biased and Hicks-neutral innovations within firms.

To summarise, offshoring positively affects total factor productivity of Swedish firms. This is particularly observed for domestic firms with low value added and foreign-owned firms with high value added/high employment/high offshoring intensity. The magnitudes of this effect are larger for domestic firms with low value added. Past skill-biased technological change in production and non-production activities translates into lower TFP for most types of firms, albeit with small in magnitude coefficients.

4.2 The effect of offshoring on relative skilled labor productivity in production

In Table (9), the results of estimating equation (12) over all firms are presented. We again consider three specifications of the main regression here. Neither offshoring variables nor exporting intensity have significant coefficients in any specification. The other dimensions of productivity do not have any effect on relative skilled labor productivity in production. Only past relative skilled labor productivity in production has a significant coefficient, giving support to the autroregressive nature of the evolution of productivity. We omit the second and third powers of $\ln A_{p,i(t-1)}$, as these are collinear with $\ln A_{p,i(t-1)}$ and do not have significant coefficients.

To see whether these regressions are telling the entire story, we estimate equation (12) differentiating firms by ownership, size and offshoring intensity.

The results are similar to the above for regressions by ownership and size in Table (10) and Table (22) in the Appendix, with several changes. Past TFP has a significant positive effect for low value added/low employment foreign-owned firms and a significant negative coefficient for high value added/high employment foreign-owned firms. Moreover, these effects are high in magnitude, where a 1% increase in past TFP is associated with a $4-5\%$ increase in relative skilled labor productivity in production for small foreign-owned firms, and an around 2% decrease - for large foreign-owned firms.

When we differentiate between low and high offshoring intensity firms in Table (11), we find significant positive effects of offshoring on both domestic and foreign-owned firms with low offshoring intensity. The coefficients on offshoring are very high, implying a 122% increase in relative skilled labor productivity in response to a 1% increase in offshoring intensity for domestic firms, and a 192% increase - for foreign-owned firms with low offshoring intensity. The differential effect of offshoring on skill-biased technological change depending on offshoring intensity of firms is reminiscent of the predictions in Acemoglu et al. (2015), who argue that offshoring will induce skill-biased technological change at low levels, but unskilled-biased change at higher levels. However, their conclusions hinge on general equilibrium effects of rising offshoring, whereas we implicitly rely on partial equilibrium, firm-specific mechanisms.

Overall, we find evidence that offshoring leads to skill-biased technological improvements in production for firms with low offshoring intensity, both domestic and foreign-owned. There is mixed evidence about the effects of the other dimensions of productivity on relative skilled labor productivity in production, where the enhancement in these may lead to slower or faster skill-biased change in production.

Table 9: Estimating equation (12) over all firms

Dependent variable: $\ln A_{p,it}$	(1)	(2)	(3)
$\ln off_{i(t-1)}$	-0.065	-0.075	
	(0.522)	(0.513)	
$\ln exp_{i(t-1)}$	-0.109	-0.039	-0.122
	(0.521)	(0.533)	(0.466)
$\ln A_{p,i(t-1)}$	0.414***	0.421***	0.414***
	(0.019)	(0.024)	(0.020)
$\omega_{i(t-1)}$	-0.433	-0.655	-0.433
	(0.412)	(0.549)	(0.410)
$\ln A_{n,i(t-1)}$	0.015	0.008	0.015
	(0.020)	(0.030)	(0.019)
$offdum_{i(t-1)}$			0.103
			(0.100)
Constant	0.205***	0.223***	0.202***
	(0.030)	(0.036)	(0.031)
Observations	18550	13680	18550
R^2	0.208	0.222	0.209

Specification (1) - all observations, specification (2) - only non-zero offshoring,

specification (3) - offshoring dummy as explanatory variable.

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Estimating equation (12) by ownership and size (value added)

	Low value added, domestic	High value added, domestic	Low value added, foreign	High value added, foreign
$\ln off_{i(t-1)}$	0.097	0.246	-7.957	-0.017
	(4.352)	(0.865)	(10.197)	(0.702)
$\ln exp_{i(t-1)}$	-2.209	-0.065	1.555	0.270
	(1.465)	(0.548)	(4.991)	(0.807)
$\ln A_{p,i(t-1)}$	0.429***	0.375***	0.346***	0.448***
	(0.050)	(0.024)	(0.098)	(0.032)
$\omega_{i(t-1)}$	-0.336	-0.281	4.187*	-1.707***
	(0.853)	(0.676)	(2.340)	(0.595)
$\ln A_{n,i(t-1)}$	-0.028	0.016	0.241	-0.042
	(0.051)	(0.019)	(0.349)	(0.048)
Constant	0.068	0.211***	0.291	0.255***
	(0.095)	(0.035)	(0.289)	(0.060)
Observations	3046	9069	451	5955
R^2	0.264	0.219	0.324	0.257

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Estimating equation (12) by ownership and offshoring intensity

	Low offshoring, domestic	High offshoring, domestic	Low offshoring, foreign	High offshoring, foreign
$\ln off_{i(t-1)}$	121.756*	0.165	191.591**	-0.081
	(68.876)	(0.774)	(93.479)	(0.649)
$\ln exp_{i(t-1)}$	-0.251	-0.477	0.858	-0.197
	(1.056)	(0.580)	(2.052)	(0.936)
$\ln A_{p,i(t-1)}$	0.368***	0.429***	0.386***	0.447***
	(0.041)	(0.030)	(0.056)	(0.034)
$\omega_{i(t-1)}$	-0.315	-0.200	-0.757	-0.954
	(0.945)	(0.454)	(1.167)	(0.711)
$\ln A_{n,i(t-1)}$	0.005	0.012	0.035	-0.003
	(0.038)	(0.025)	(0.141)	(0.048)
Constant	0.150**	0.189***	0.253*	0.262***
	(0.068)	(0.042)	(0.146)	(0.061)
Observations	4597	7518	1154	5252
R^2	0.232	0.231	0.280	0.250

Offshoring stands for offshoring intensity

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 The effect of offshoring on relative skilled labor productivity in non-production activities

In Table (12), the results of estimating equation (13) over all industries jointly are presented. We consider three possible specifications here, and omit the second and third powers of $\ln A_{n,i(t-1)}$, as they are collinear with $\ln A_{n,i(t-1)}$.

Offshoring variables do not exhibit significant effects in any specification. Exporting intensity has a significant positive coefficient in specifications (1) and (2), implying that intensified exporting leads to skill-biased technological change. Past relative skilled labor productivity in non-production has high significant positive coefficients in all specifications. Past TFP has no significant effects, while past skill-biased technological change in production has a significant positive coefficient in all specifications, albeit small in magnitude. The latter result supports the idea that there are spillovers between skill-biased improvements in productivity in production and non-production activities of firms.

Let us investigate equation (13) by ownership and size of firms. In Table (13), neither offshoring intensity nor other dimensions of productivity have significant effects on $\ln A_{n,it}$. Only for high value added foreign-owned firms does past relative skilled labor productivity in production have a significant positive coefficient.

Next, we re-run these regressions in Table (14), using the offshoring dummy rather than offshoring intensity as an explanatory variable. Now offshoring has a significant positive coefficient for high value added domestic firms, and switching from not offshoring to offshoring leads to a 0.15% increase in relative skilled labor productivity in non-production activities. The results are similar when we measure size by the number of employees in Table (23) in the Appendix. Particularly, switching from not offshoring to offshoring leads to a 0.13% increase in relative skilled labor productivity in non-production activities for high employment domestic firms.

Table 12: Estimating equation (13) over all firms

Dependent variable: $\ln A_{n,it}$	(1)	(2)	(3)
$\ln off_{i(t-1)}$	0.023	0.022	
	(0.129)	(0.121)	
$\ln exp_{i(t-1)}$	0.224*	0.362***	0.218
	(0.136)	(0.134)	(0.150)
$\ln A_{n,i(t-1)}$	0.457***	0.451***	0.456***
	(0.014)	(0.016)	(0.014)
$\omega_{i(t-1)}$	-0.077	-0.052	-0.077
	(0.076)	(0.079)	(0.065)
$\ln A_{p,i(t-1)}$	0.004*	0.005***	0.004**
	(0.002)	(0.002)	(0.002)
$offdum_{i(t-1)}$			0.063
			(0.042)
Constant	0.063***	0.071***	0.061***
	(0.009)	(0.010)	(0.008)
Observations	19305	14242	19305
R^2	0.243	0.264	0.243

Specification (1) - all observations, specification (2) - only non-zero offshoring, specification (3) - offshoring dummy as explanatory variable.

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Estimating equation (13) by ownership and size (value added)

	Low value added, domestic	High value added, domestic	Low value added, foreign	High value added, foreign
$\ln off_{i(t-1)}$	1.093	0.289	-1.022	-0.009
	(1.641)	(0.461)	(1.423)	(0.119)
$\ln exp_{i(t-1)}$	0.076	0.281	-0.127	0.182
	(0.511)	(0.197)	(0.754)	(0.177)
$\ln A_{n,i(t-1)}$	0.425***	0.460***	0.486***	0.495***
	(0.036)	(0.015)	(0.078)	(0.030)
$\omega_{i(t-1)}$	-0.010	-0.092	-0.455	-0.007
	(0.174)	(0.115)	(0.457)	(0.104)
$\ln A_{p,i(t-1)}$	-0.005	0.004	0.003	0.005**
	(0.006)	(0.003)	(0.011)	(0.002)
Constant	0.049*	0.068***	0.011	0.064***
	(0.027)	(0.014)	(0.064)	(0.013)
Observations	3286	9386	484	6115
R^2	0.223	0.251	0.506	0.339

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Estimating equation (13) by ownership and size (value added), with offshoring dummy instead of offshoring intensity

	Low value added, domestic	High value added, domestic	Low value added, foreign	High value added, foreign
$offdum_{i(t-1)}$	-0.017	0.150*	0.069	-0.075
	(0.168)	(0.078)	(0.348)	(0.107)
$\ln exp_{i(t-1)}$	0.851	0.354*	-0.538	0.224
	(0.741)	(0.201)	(0.712)	(0.174)
$\ln A_{n,i(t-1)}$	0.379***	0.447***	0.467***	0.491***
	(0.052)	(0.018)	(0.089)	(0.029)
$\omega_{i(t-1)}$	0.146	-0.045	-0.517	0.001
	(0.227)	(0.112)	(0.459)	(0.096)
$\ln A_{p,i(t-1)}$	-0.005	0.005	0.012	0.006***
	(0.007)	(0.003)	(0.012)	(0.002)
Constant	0.010	0.068***	-0.001	0.075***
	(0.057)	(0.016)	(0.087)	(0.015)
Observations	1424	6707	386	5697
R^2	0.281	0.261	0.582	0.355

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Estimating equation (13) by ownership and offshoring intensity, with offshoring dummy instead of offshoring intensity

	Low offshoring, domestic	High offshoring, domestic	Low offshoring, foreign	High offshoring, foreign
$offdum_{i(t-1)}$	-0.015	0.140**	0.046	-0.051
	(0.073)	(0.057)	(0.141)	(0.108)
$\ln exp_{i(t-1)}$	-0.348	0.408*	0.265	0.108
	(0.460)	(0.220)	(0.341)	(0.204)
$\ln A_{n,i(t-1)}$	0.469***	0.427***	0.516***	0.482***
	(0.029)	(0.019)	(0.047)	(0.028)
$\omega_{i(t-1)}$	-0.051	0.039	-0.208	-0.052
	(0.125)	(0.135)	(0.185)	(0.123)
$\ln A_{p,i(t-1)}$	0.002	-0.001	0.009*	0.005**
	(0.004)	(0.004)	(0.005)	(0.002)
Constant	0.059***	0.064***	0.013	0.072***
	(0.021)	(0.014)	(0.029)	(0.015)
Observations	4802	7870	1201	5398
R^2	0.242	0.244	0.386	0.340

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When we differentiate firms by offshoring intensity in Table (15), we see that switching into offshoring has a similar in magnitude positive effect for high offshoring intensity domestic firms. Past skill-biased change in production has a significant positive effect on skill-biased change in non-production activities for foreign-owned firms.

To summarise, initiating offshoring is associated with future skill-biased technological improvements in non-production activities of domestic firms with high value added/high employment/high offshoring intensity. Skill-biased technological change in production has positive spillovers to skill-biased technological change in non-production activities of foreign-owned firms.

5 An Alternative Model

While estimating the effects of offshoring on TFP and skill-biased technological change in a unified framework seems to be a reasonable approach that produces plausible results, the question remains whether it is necessary. That is, does estimating the effects of offshoring in this manner change our conclusions in any way? To answer this question, we fit an alternative model to our data. It replicates the approach of the literature on the effect of offshoring on TFP, where TFP is first obtained from production data, and then regressed on offshoring and control variables. The control variables include all of the variables we introduced in the baseline model, except past relative skilled labor productivity in production and non-production activities.

The production function in logs is the same as that above:

$$y_{it} = \alpha_k k_{it} + \alpha_p l^u_{p,it} + \beta_p x_{p,it} + \alpha_n l^u_{n,it} + \beta_n x_{n,it} + \omega_{it} + u_{it},$$

where the lower case letters denote the logarithms of the upper case variables, and

$$L_{j,it} = X_{j,it}^{-\frac{\sigma_j}{\sigma_j - 1}} L^u_{j,it}, \quad X_{j,it} \equiv \frac{W^u_t L^u_{j,it}}{W^s_t L^s_{j,it} + W^u_t L^u_{j,it}}, \quad \text{for} \quad j = p, n.$$

Total factor productivity follows the dynamics

$$\omega_{it} = \xi_t + \gamma_1\omega_{i(t-1)} + \gamma_2\omega^2_{i(t-1)} + \gamma_3\omega^3_{i(t-1)} + \gamma_4 \ln off_{i(t-1)} + \gamma_5 \ln exp_{i(t-1)} + \nu_{it}, \quad (14)$$

where ξ_t is an industry-specific total factor productivity shock, $off_{it} \equiv \ln(1+\frac{M^f_{it}}{M_{it}})$ and $exp_{it} \equiv \ln(1+\frac{E_{it}}{Y_{it}})$ are logged offshoring intensity and logged exporting intensity of firm i in year t, respectively, and ν_{it} is a firm-specific zero-mean shock to ω in year t, which is unforeseen before year t and is independent of ξ_t.

We estimate this model using a two-stage estimation approach similar to that above, and applying GMM with 5 moment conditions

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \beta_p, \beta_n)k_{it}] = 0,$$

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \beta_p, \beta_n)l^u_{p,i(t-1)}] = 0,$$

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \beta_p, \beta_n)x_{p,i(t-1)}] = 0,$$

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \beta_p, \beta_n)l^u_{n,i(t-1)}] = 0,$$

$$E[\nu_{it}(\alpha_k, \alpha_p, \alpha_n, \beta_p, \beta_n)x_{n,i(t-1)}] = 0,$$

to identify the parameters $\alpha_k, \alpha_p, \alpha_n, \beta_p, \beta_n$. Once the estimates of TFP ω_{it} are obtained, we estimate equation (14), adding the non-selection hazard ratio, calculated in the same way as in the baseline model, as an explanatory variable:

$$\begin{aligned}\omega_{it} = \xi_t &+ \gamma_1\omega_{i(t-1)} + \gamma_2\omega^2_{i(t-1)} + \gamma_3\omega^3_{i(t-1)} + \gamma_4 \ln off_{i(t-1)} + \gamma_5 \ln exp_{i(t-1)} \\ &+ \gamma_6 nsh(X\hat{\delta}) + \nu_{it}. \end{aligned} \quad (15)$$

The results are presented in Table (16). One can immediately see that the results are dramatically different from those in the baseline model (Table (6)), in that the coefficients on offshoring intensity in specifications (1) and (2) are no longer statistically significant. Exporting intensity still has significant positive coefficients in all specifications, and these are close in magnitude to the values in the baseline estimation.

We test how different the results of the two models are by bootstrapping. That is, we draw random samples with replacement from our dataset, fit the two models (baseline and alternative) to these samples, run regressions (11) and (15) in three specifications[10], and take the difference between the coefficients on offshoring and exporting in the baseline model and the alternative model. As is shown in Table (17), the coefficient on offshoring intensity in specifications (1) and (2) is statistically significantly larger in regression (11) than in regression (15). The difference between the coefficients on the offshoring dummy is not statistically significant in specification (3). The coefficient on exporting intensity is not statistically significantly different across the two models, in any specification, as demonstrated in Table (18).

The fact that offshoring intensity has a statistically significantly larger coefficient in the baseline model than in the alternative model, where TFP is the sole focus of estimation, has important implications. Researchers and policy-makers may settle on misleading conclusions about the effect of offshoring on TFP, which might affect future policy recommendations or policy debates.

6 Conclusion

Existing literature on the effects of offshoring on firm productivity and relative skilled labor demand treats these two questions individually. For the first time, we propose a model where offshoring can influence both firms' total factor productivity and skill-biased technological change, and through it relative skilled labor demand. This has implications for the estimation results. We find significant positive effects of offshoring on total factor productivity in our model, whereas an alternative framework where only TFP is considered, delivers no effects of offshoring. Our model allows

[10] We make sure that we run these regressions only on observations that are used by both regressions, so that the difference between the coefficient values is not caused by the fact that $\ln A_{p,i(t-1)}$ and $\ln A_{n,i(t-1)}$ have to be observed to apply regression (11), but can be missing when we run regression (15).

for an impact of offshoring on relative skilled labor productivities in production and non-production activities, as well as for interaction between different dimensions of productivity. The Swedish data confirms that these relationships are relevant, and therefore properly evaluating the effect of offshoring on any productivity dimension requires fitting the fully-fledged model.

Our conclusion is similar in spirit to the message of De Loecker (2013), who argues that correctly gauging the impact of exporting on productivity necessitates introducing this relationship into the model when estimating TFP. Not doing so creates a bias, and a researcher may find no significant effect of exporting. We claim that estimating the effect of offshoring on different dimensions of productivity has to be done jointly in a unified framework, where spillovers between them are also allowed.

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Table 16: Estimating equation (15), over all firms

Dependent variable: ω_{it}	(1)	(2)	(3)
$\ln off_{i(t-1)}$	-0.010	-0.011	
	(0.027)	(0.027)	
$\ln exp_{i(t-1)}$	0.061	0.050	0.060
	(0.014)***	(0.015)***	(0.013)***
$\omega_{i(t-1)}$	0.332	0.351	0.332
	(0.023)***	(0.032)***	(0.023)***
nsh_{it}	0.169	0.143	0.168
	(0.035)***	(0.046)***	(0.034)***
$offdum_{i(t-1)}$			0.001
			(0.003)
Constant	0.002	0.004	0.002
	(0.001)*	(0.001)***	(0.001)*
Observations	31602	18531	31602
R^2	0.499	0.529	0.499

Specification (1) - all observations, specification (2) - only non-zero offshoring, specification (3) - offshoring dummy as explanatory variable.

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Summary of differences in coefficients on offshoring variable between equations (11) and (15)

Variable	Mean	Median	St. dev.	Min	Max	5th pctile	95th pctile
Difference in (1)	.011	.011	.006	.001	.023	.002	.022
Difference in (2)	.012	.013	.006	.003	.023	.003	.023
Difference in (3)	-0.0004	-.0007	.003	-.006	.005	-.005	.005

Difference in (k) stands for difference in specification (k), $k = 1, 2, 3$

Table 18: Summary of differences in coefficients on exporting intensity between equations (11) and (15)

Variable	Mean	Median	St. dev.	Min	Max	5th pctile	95th pctile
Difference in (1)	-.011	-.009	.01	-.034	.003	-.03	.003
Difference in (2)	-.009	-.008	.013	-.036	.007	-.036	.007
Difference in (3)	-.01	-.009	.01	-.034	.003	-.03	.003

Difference in (k) stands for difference in specification (k), $k = 1, 2, 3$

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7 Appendix

Table 19: Distribution of firms according to industry classification

Industry	NACE Revision 2 Description	Frequency	Percent
10-12	Food products, beverages and tobacco	257	8.80
13-15	Textiles, wearing apparel, leather and related products	59	2.02
16	Wood and products of wood and cork	253	8.66
17	Paper and paper products	96	3.29
18	Printing and reproduction of recorded media	129	4.41
20-21	Chemicals and chemical products	134	4.59
22	Rubber and plastics products	177	6.06
23	Other non-metallic mineral products	94	3.22
24	Basic metals	62	2.12
25	Fabricated metal products, except machinery and equipment	599	20.50
26	Computer, electronic and optical equipment	92	3.15
27	Electrical equipment	126	4.31
28	Machinery and equipment n.e.c.	437	14.96
29	Motor vehicles, trailers and semi-trailers	154	5.27
30	Other transport equipment	44	1.51
31-32	Furniture, other manufacturing	209	7.15
Total		2922	100

Based on the dataset used for estimation

Table 20: Estimating equation (11) with lagged R&D intensity, over all firms

Dependent variable: ω_{it}	(1)	(2)	(3)
$\ln off_{i(t-1)}$	0.038	0.039	
	(0.081)	(0.062)	
$\ln exp_{i(t-1)}$	0.089	0.081	0.086
	(0.089)	(0.086)	(0.084)
$\omega_{i(t-1)}$	0.392***	0.385***	0.392***
	(0.072)	(0.074)	(0.080)
$\ln A_{p,i(t-1)}$	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.001)
$\ln A_{n,i(t-1)}$	-0.009*	-0.010*	-0.009
	(0.005)	(0.005)	(0.005)
$rnd_{i(t-1)}$	-0.003	-0.006	-0.003
	(0.005)	(0.005)	(0.005)
nsh_{it}	-0.103	-0.114	-0.118
	(0.239)	(0.246)	(0.238)
$offdum_{i(t-1)}$			0.014
			(0.019)
Constant	0.050***	0.050***	0.050***
	(0.005)	(0.005)	(0.005)
Observations	1738	1651	1738
R^2	0.516	0.518	0.516

Specification (1) - all observations, specification (2) - only non-zero offshoring, specification (3) - offshoring dummy as explanatory variable.

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Estimating equation (11) by ownership and size (employment)

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	Low employment, domestic	High employment, domestic	Low employment, foreign	High employment, foreign
$\ln off_{i(t-1)}$	0.190	0.020	0.041	0.061**
	(0.166)	(0.087)	(0.217)	(0.030)
$\ln exp_{i(t-1)}$	0.077*	0.084***	0.024	0.016
	(0.045)	(0.022)	(0.143)	(0.030)
$\omega_{i(t-1)}$	0.394***	0.313***	0.151	0.452***
	(0.035)	(0.037)	(0.121)	(0.048)
$\ln A_{p,i(t-1)}$	-0.002**	-0.002**	0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)
$\ln A_{n,i(t-1)}$	-0.002	-0.002*	0.005	-0.003
	(0.002)	(0.001)	(0.010)	(0.002)
nsh_{it}	0.291***	0.218***	-0.259	0.199*
	(0.085)	(0.080)	(0.317)	(0.104)
Constant	0.009***	0.005***	0.020**	0.007**
	(0.003)	(0.002)	(0.008)	(0.003)
Observations	3404	8587	490	5522
R^2	0.573	0.584	0.589	0.588

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Estimating equation (12) by ownership and size (employment)

	Low employment, domestic	High employment, domestic	Low employment, foreign	High employment, foreign
$\ln off_{i(t-1)}$	-0.279	0.551	-18.049	0.202
	(1.275)	(1.232)	(12.358)	(0.669)
$\ln exp_{i(t-1)}$	-3.113**	0.255	4.280	-0.063
	(1.286)	(0.589)	(4.337)	(0.843)
$\ln A_{p,i(t-1)}$	0.361***	0.409***	0.291***	0.459***
	(0.044)	(0.033)	(0.081)	(0.027)
$\omega_{i(t-1)}$	-0.355	-0.419	4.736**	-1.798***
	(0.798)	(0.653)	(2.157)	(0.617)
$\ln A_{n,i(t-1)}$	-0.024	0.013	0.140	-0.026
	(0.051)	(0.024)	(0.316)	(0.041)
Constant	0.141**	0.186***	0.206	0.263***
	(0.069)	(0.037)	(0.299)	(0.057)
Observations	3257	8858	504	5902
R^2	0.192	0.250	0.312	0.275

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Estimating equation (13) by ownership and size (employment), with offshoring dummy instead of offshoring intensity

	Low employment, domestic	High employment, domestic	Low employment, foreign	High employment, foreign
$offdum_{i(t-1)}$	0.089	0.133*	0.406	-0.077
	(0.168)	(0.079)	(0.313)	(0.100)
$\ln exp_{i(t-1)}$	1.599**	0.174	0.040	0.201
	(0.635)	(0.209)	(0.539)	(0.187)
$\ln A_{n,i(t-1)}$	0.413***	0.434***	0.530***	0.488***
	(0.045)	(0.019)	(0.079)	(0.031)
$\omega_{i(t-1)}$	0.077	-0.013	-0.588	0.003
	(0.203)	(0.114)	(0.366)	(0.094)
$\ln A_{p,i(t-1)}$	-0.001	0.003	0.009	0.006**
	(0.008)	(0.003)	(0.010)	(0.002)
Constant	-0.006	0.070***	-0.061	0.076***
	(0.056)	(0.016)	(0.072)	(0.013)
Observations	1555	6576	446	5637
R^2	0.292	0.253	0.627	0.353

Firm fixed effects and industry-year fixed effects are included

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$