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PRODUCTIVITY EFFECTS OF INTERNATIONALISATION THROUGH THE DOMESTIC SUPPLY CHAIN: EVIDENCE FROM EUROPE

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Productivity Effects of Internationalisation Through the Domestic Supply Chain: Evidence from Europe*

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Abstract

This paper analyses whether indirect effects of internationalisation occur through the domestic supply chain. We investigate productivity effects for a given firm resulting from the import or export of intermediate inputs by domestic upstream and downstream industries. Using a rich sample of manufacturing firms in 19 EU countries, we find evidence that domestic access to intermediate inputs that are also destined to foreign countries is associated with higher levels of revenue productivity. Further, our results highlight two common, but important, misspecification biases: ignoring the dynamic nature of productivity and estimating a value-added instead of a gross-output production function.

Keywords: Offshoring, Inshoring, Supply Chain, Total Factor Productivity, Trade, Learning
JEL classification: D22, D24, D57, D83, F14, L25

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1 Introduction

Increased opportunities for international trade have led to a large literature which examines the effect of export and import behaviour on future productivity. Export-related productivity improvements—termed "learning by exporting"—have been explained by several mechanisms. These include product innovation and process upgrading, as well as improvements in technical standards, managerial practices, and inventory techniques.[1] "Learning by importing" on the other hand, contributes to firms' productivity through access to foreign-sourced intermediate inputs which are differentiated from those available on the domestic market. These inputs can, in turn, lead to knowledge transfer, access to more varieties, and cost saving from process and product innovation. Through complementing domestic inputs, they can also boost efficiency of the domestic component of production processes.[2]

Over the past decades, decreases in trade and communication costs have resulted in increased fragmentation of production, both within and across national boundaries (Antràs et al. 2012). Yet, while a substantial amount of research examines the productivity effects of firms' or industries' offshoring behaviour[3] (e.g. Amiti and Wei 2005; Amiti and Konings 2007; Tomiura 2007; Halpern et al. 2015), potential productivity effects of offshoring along the domestic supply chain have received less attention. One notable exception is Blalock and Veloso (2007), who focus on increased competition faced by suppliers of domestic intermediate goods due to offshoring by their clients. They find evidence that vertical supply chain relationships serve as a channel through which indirect import-driven productivity upgrading occurs in Indonesia.

In addition to examining this direct, import-driven channel across 19 EU countries over the period 2000-2014, we explore potential productivity effects for a given firm when its suppliers also export intermediate goods abroad. As such, as an analogue to offshoring, we define 'inshoring' as the export of intermediate goods to both affiliated and unaffiliated foreign firms.[4] If inshoring increases the quality and range of the set of domestically available intermediate inputs, a given local client may experience a boost to its productivity. Next, to cover all possible channels, we expand our analysis to indirect channels of offshoring and inshoring. Specifically, we first examine whether sourcing from local suppliers that offshore are associated with pass-on productivity effects for a given firm. Second, we assess whether pass-on productivity effects are also associated with supplying local clients that inshore.

[1] Van Biesebroeck (2005) and De Loecker (2007) examine learning by exporting effects. Prominent papers which can explain these effects include those by Clerides et al. (1998), Fernandes (2007), Lileeva and Trefler (2010) and Kasahara and Lapham (2013).

[2] Amiti and Konings (2007) and Kasahara and Rodrigue (2008) examine learning by importing effects. Papers such as those by Markusen (1989), Grossman and Helpman (1991), Bas and Strauss-Kahn (2015), Halpern et al. (2015) and Antràs et al. (2017) present explanations of these effects in line with those referred to above.

[3] Our notion of offshoring includes both international outsourcing and also production transfers within MNCs. See Crinò (2009) for an overview of definitions.

[4] The term was initially inspired by Slaughter (2004) who used "insourcing" to refer to subsidiaries of foreign-headquartered multinationals, while Liu and Trefler (2008) coined the term as the flip side of offshore outsourcing, i.e. the sale of services to unaffiliated foreign firms.

Our analysis sheds light on potential productivity effects to a given firm associated with the internationalisation behaviour of its local clients and suppliers. Since firms are more likely to share new knowledge with related parties along the supply chain than with competitors (Blalock and Veloso 2007), we focus on the inter-industry productivity effects of offshoring and inshoring. Local firms may then experience indirect productivity effects of internationalisation through participation in the domestic supply chain. The mechanisms we have in mind bear close resemblance to vertical productivity effects from foreign direct investment (FDI), as in Javorcik (2004) and Blalock and Gertler (2008). In our case, however, the conduit is offshoring and inshoring by vertically related firms and not FDI.

On the one hand, it has been shown extensively that firms can learn from performing tasks such as organisational restructuring, network sharing, revamping technical and managerial practices, and transferring knowledge (Arrow 1962; Stokey 1988; Parente 1994; Jovanovic and Nyarko 1996). Indirect competition pressure may also incite firms to innovate, upgrade quality, and save costs. In our analysis, we also associate this learning process with supplying (sourcing) intermediate inputs to upstream (from downstream) sectors that also inshore or offshore. On the other hand, it has been shown that learning can be relationship-specific when production requires the coordination of inputs from multiple firms (Kellogg 2011). This includes both knowledge accumulation and personal interactions between producers and providers of intermediate-inputs who work together in a contracting relationship. Given these mechanisms, we therefore empirically model potential productivity effects from inter-industry offshoring and inshoring as a learning process in the production function, where past experience from such channels affects current productivity.

As in most empirical research which addresses firm performance, productivity measurement is a core component in our analysis. The approach we use follows that of Gandhi, Navarro, and Rivers (2018) (herein GNR), whose estimation method of gross output production functions both controls for endogeneity and value-added bias found in other estimators[5] and allows for the inclusion of firm fixed effects. In addition to adopting this approach, we point to a common specification bias in previous applied work which arises when ignoring the dynamic nature of productivity.

For this analysis, we combine a rich micro-level dataset for firms in the manufacturing sector with input-output (IO) tables. Our firm-level dataset contains all balance sheet information necessary for the estimation of the firms' production function (and hence productivity). IO-tables are then used to construct industry-country-specific measures of inter-industry offshoring and inshoring intensities crucial to our analysis. Moreover, our consideration of a broad set of countries lends itself to strong external validity of our results, as the 19 EU countries differ across various dimensions: geography; economic development; types of institutions; trade

[5]See Section 3 for a detailed description of identification issues which arise when using proxy variable methods which are prevalent in the literature yet do not allow for the estimation of gross output production functions with at least one flexible input.

openness/integration; etc.

We find that sourcing from domestic industries that also export intermediates is associated with higher productivity levels of a given firm (termed as upstream inshoring). This prevails as the only robust channel through which inter-industry productivity effects occur.[6] We posit that the observed effect stems from access to higher quality/superior inputs which are also exported. Nonetheless, this need not be the only mechanism driving our observed outcome, as our results capture any potential learning process arising from the channel of upstream inshoring.

Based on our results, a one standard deviation increase in upstream inshoring is associated with a productivity increase of 1.13% in the short run and 2.50% in the long run. This result serves as a potential explanation of the finding of Amiti and Konings (2007), where, on average, even non-importing firms benefit from tariff reductions. Our results indicate that the domestic supply chain can facilitate indirect productivity effects from internationalisation. Exploring further heterogeneity, we find these effects to be stronger for firms and industries that are less likely to be already internationally involved. Specifically, our results suggest that the effect is more prominent for firms without foreign ownership links and for firms in industries which are relatively downstream and/or low-tech and/or capital intensive. Lastly, we confirm important biases which arise when ignoring the dynamic nature of productivity and specifying a value-added rather than a gross-output production function.

The remainder of this paper is organised as follows. In Section 2 we discuss inter-industry offshoring and inshoring and present how the proxies used throughout our analysis are constructed. In Section 3 we describe our empirical methodology with a focus on how we correct for biases in productivity estimates which are common in the literature. Section 4 describes the data and Section 5 presents results, including an analysis of potential biases and an exploration of various forms of heterogeneity. Finally, Section 6 concludes.

2 Inter-industry Offshoring and Inshoring

To measure inter-industry offshoring and inshoring activities, we construct proxies at the industry-country-year level using Input-Output (IO) tables from the World Input-Output Database (WIOD) (*cf. infra*). Figure 1 illustrates the different channels for which we create proxies. For notational simplicity, we suppress the country-c subscript from this section.

A firm is confronted with downstream offshoring when local clients start to import intermediates previously sourced at home (see steps 2 & 5 in Figure 1). Downstream offshoring thus captures downstream demand side shocks or import competition. Firms then face foreign competition to supply differentiated intermediate inputs to downstream industries. To survive and remain competitive, these firms need to reduce costs and improve productivity. Should the

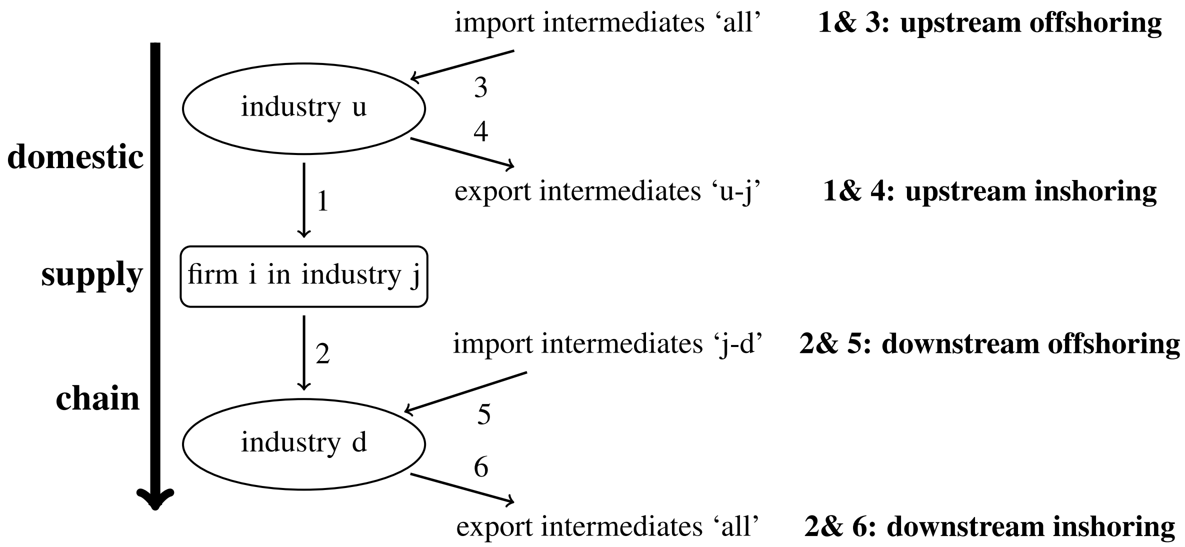
[6] Our results also validate to some extent the channel explored in Blalock and Veloso (2007). However, they are not robust to the specification including country-time fixed effects which are necessary due to the presence of multiple countries in our dataset (unlike for their analysis that includes one country only).

intermediates be complements to those offshored by downstream firms, productivity effects may result from upgrading production processes in order to match specificities and quality standards of the complementary intermediate inputs used in the production process of downstream firms (see Blalock and Veloso 2007). To capture downstream offshoring, we build on a measure introduced by Merlevede and Michel (2013):

$$OFFdown_{jt} = \sum_{d \neq j} \theta_{jdt} \Phi_{jdt} \tag{1}$$

where Φ_{jdt} is the offshoring intensity in industry d of products that industry j supplies to downstream industry d in year t; it is calculated as the share of imported intermediates in total intermediates sourced from j by d. Φ_{jdt} thus measures the offshoring behaviour of downstream industry d that directly affects (firms in) industry j. We obtain a value of Φ for all possible industry pairs involving a given industry j and use θ_{jdt} to generate a single value for $OFFdown_{jt}$ as a weighted average of Φs. More precisely θ_{jdt} is the proportion of industry j's domestic supply sold to downstream industry d in year t. θs are calculated from the domestic IO-table.

Figure 1: Illustration of inter-industry offshoring and inshoring



Similarly, we define 'upstream inshoring' for a given firm as sourcing intermediates from (a firm in) an industry that also exports the same intermediate goods (see steps 1 & 4 in Figure 1). For instance, think of a firm in the Manufacture of Computer, Electronic and Optical Production industry that supplies intermediate inputs to a firm in the Manufacture of Electrical Equipment industry. When the former also exports these products for intermediate use abroad, i.e. inshores, this may affect the productivity of the latter because of the availability of higher quality domestic inputs. Potential productivity effects may also extend to more indirect mechanisms such as diffusion of management practices, benefits from international networking, and organisational restructuring. To analyse such effects we define upstream inshoring, $INup_{jt}$, as:

$$INup_{jt} = \sum_{u \neq j} \zeta_{jut} \Psi_{jut} \tag{2}$$

where Ψ_{jut} measures the inshoring activity of upstream industry u with respect to products that industry j uses as intermediate inputs. Inshoring intensities are calculated as the share of exported intermediates in the total amount of intermediates delivered by u. We average Ψs over partner industries u using ζ_{jut}, defined as the proportion of industry j's domestically sourced intermediate inputs from upstream industries u at time t, to obtain $INup_{jt}$.

In addition to the aforementioned direct channels which are based on intermediates common to industry j and its partner industries, we analyse two further forms of indirect internationalisation through domestic supply chain participation. This includes potential productivity effects from upstream offshoring and downstream inshoring, where no product-specific links are at play. However, offshoring in a previous stage or inshoring in a subsequent stage of the supply chain may also result in indirect productivity spillover effects similar to those above. Upstream offshoring is a supply side effect originating from the import of intermediate inputs by a firm's suppliers (see steps 1 & 3 in Figure 1). In this case, the learning mechanisms rely on knowledge diffusion from upstream to downstream industries (Grossman and Helpman 1995; Coe and Helpman 1995; Connolly 2003). Downstream inshoring effects may result from the demand for increased quality of intermediate inputs from export oriented downstream clients (see steps 2 & 6 in Figure 1).

To analyse such effects we define upstream offshoring as:

$$OFFup_{jt} = \sum_{u \neq j} \zeta_{jut} \Omega_{ut} \tag{3}$$

where ζ_{jut} is again the proportion of industry j's intermediate inputs sourced from upstream industries u at time t. Ω_{ut} is the 'overall' offshoring intensity in industry u, averaged over all products since in this case there is no direct product link between industries j and u.

Downstream inshoring is then defined as:

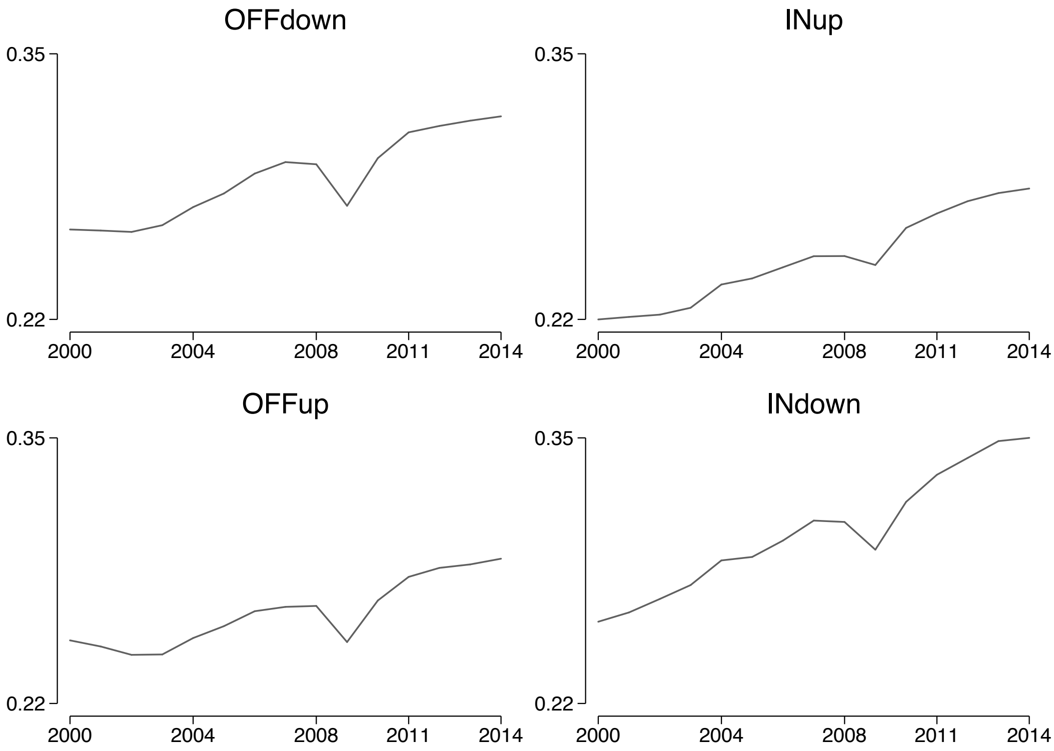
$$INdown_{jt} = \sum_{d \neq j} \theta_{jdt} \Theta_{dt} \tag{4}$$

where Θ_{dt} measures the inshoring intensities of downstream industries d and θ_{dt} is defined as above.

Furthermore, our empirical model discussed in section 3 includes intra-industry offshoring (OFF) and inshoring (IN) intensities among the explanatory variables. We think of them as important control variables for two principal reasons. First, our firm-level data do not allow us to determine firm-specific offshoring and inshoring intensities and the industry-level intensities are an average over firms with and without internationalisation activities. Second, our measures in (1)-(4) exclude intra-industry supply of intermediates in order to capture pure inter-industry effects. Since the industry classification in the IO-tables is fairly aggregated, within-industry supply chain relations are likely to exist and will also be reflected in industry-level offshoring and inshoring intensities. This makes the intra-industry variables important controls, but their interpretation is hampered by the fact that they reflect a net outcome of different mechanisms.

All four measures, $OFFdown_{jt}$, $INup_{jt}$, $OFFup_{jt}$, and $INdown_{jt}$, are inherently relative where firms with larger values are those in industries faced with relatively more downstream/upstream offshoring/inshoring. Figure 2 presents the average trend for each of the inter-industry variables in equations (1)-(4). The figure illustrates that for the case of the EU we find a clear upward trend across all measures with an expected decrease in the year following the 2008 financial crisis. The clear overall upward trend fits with the EU's economic history characterised by increasingly integrated economies which are heavily oriented towards intra-bloc trade in intermediates.

Figure 2: Inter-industry offshoring and inshoring by year (averaged over countries and industries)

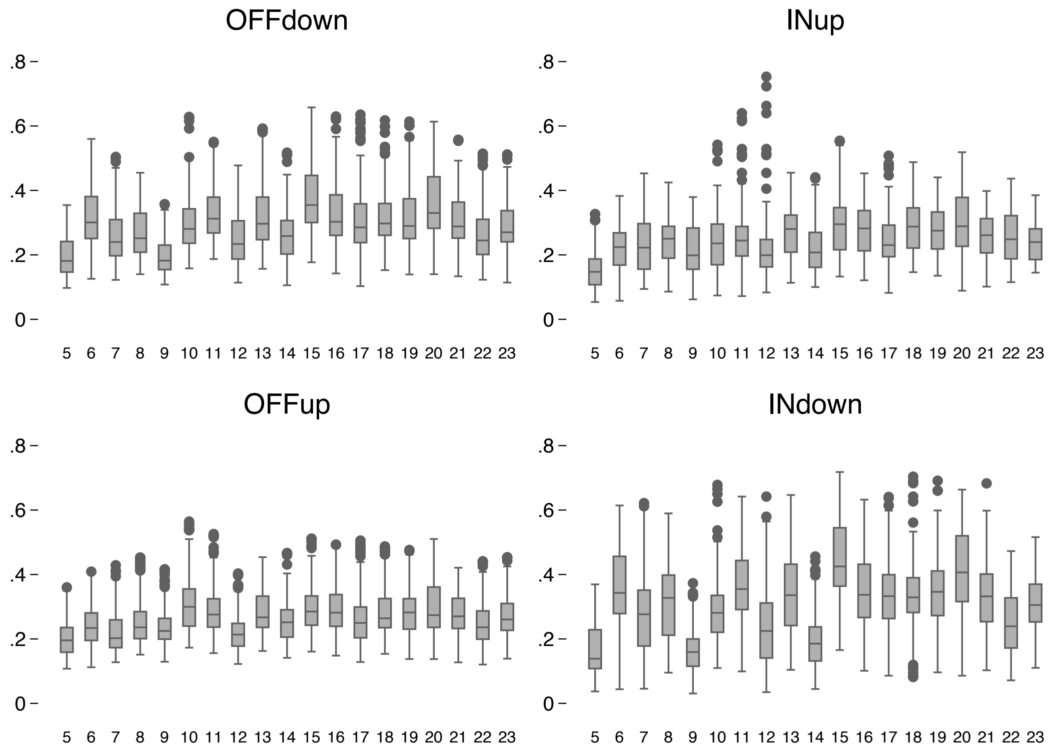


Source: Authors' calculations based on WIOT.

We observe heterogeneity in the measures originating from the country and/or industry dimension. Figure 3, for example, contains boxplots of the values for each of the variables by industry (see also Figure D.1 in Appendix D). We observe substantial variation across industries: industry 15, Manufacture of Basic Metals, together with industry 20, Manufacture of Motor Vehicles, Trailers and Semi-trailers, score high on all four variables. Industry 5, Manufacture of

Food Products, Beverages and Tobacco Products, closely followed by industry 9, Printing and reproduction of recorder media, are generally confronted with the lowest values for inter-industry internationalisation. Similarly, at the country dimension we find Hungary and Estonia to score the highest while Spain and Italy are facing the lowest values across all four measures (see Figure D.2 in Appendix D). Table 1 in the data section contains further summary statistics.

Figure 3: Inter-industry offshoring and inshoring by industry



Source: Authors' calculations based on WIOT.
Notes: Let x represent the variable of interest. The upper, middle and lower hinge of the box represents the 25th ($x_{[25]}$), 50th ($x_{[50]}$) and 75th ($x_{[75]}$) percentile, respectively. Define $x_{(i)}$ as the ith ordered value of x. The upper adjacent line has a value $x_{(i)}$ such that $x_{(i)} \leq U$ and $x_{(i+1)} > U$, where $U = x_{[75]} + 1.5(x_{[75]} - x_{[25]})$. The lower adjacent line has a value $x_{(i)}$ such that $x_{(i)} \geq L$ and $x_{(i+1)} < L$, where $L = x_{[25]} - 1.5(x_{[75]} - x_{[25]})$. Solid circles represent outside values.

3 Empirical Methodology

3.1 Total Factor Productivity

To analyse potential productivity effects of inter-industry offshoring and inshoring, we consider an industry-j specific gross-output production function $Y_{it} = F_j(K_{it}, L_{it}, M_{it})\mathrm{e}^{\omega_{it}+\varepsilon_{it}}$, with Hicks-neutral total factor productivity ω_{it} (TFP). In logs, the production function to be estimated is of the following form:

$$y_{it} = f_j(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it} \tag{5}$$

where y_{it}, k_{it} and m_{it} are log values of deflated sales, tangible fixed assets and material costs, respectively, and l_{it} is the log of the total number of employees of firm i (in industry j and country c) at time t. ω_{it} is unobserved to the econometrician but known to the firm. Ex-post shocks, i.e. after the firm's decision on which inputs to use, are picked up by ε_{it}.[7]

The applied production function estimation literature has primarily employed structural approaches including both dynamic panel methods (Arellano and Bond 1991; Blundell and Bond 1998, 2000) and proxy variable methods (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg et al. 2015). The main focus has been to solve for endogeneity, also known as 'simultaneity' or 'transmission bias.' Such bias originates from the fact that firms know their productivity level when they decide on which inputs to use (Marschak and Andrews 1944; Griliches and Mairesse 1999). Proxy variable methods have dominated in the literature given dynamic panel methods' weak performance both at a theoretical and empirical level. Despite their popularity and prevalence, proxy variable methods suffer from identification issues when the production function contains at least one flexible input such as materials. These issues have been highlighted by Mendershausen (1938); Marschak and Andrews (1944); Bond and Söderbom (2005); Ackerberg et al. (2015) and formalised by GNR. Intuitively, there is not enough variation outside the production function system to identify the flexible input.[8]

To circumvent this problem, applied economists have focused on value-added production functions where the flexible input—materials—is subtracted from output and thus 'disappears' from the production function. Such a specification, however, will fail to identify the true variable of interest, i.e. TFP, even under very strong assumptions (Bruno 1978; Diewert 1982; Basu and Fernald 1997). Estimates suffer from a value-added bias causing the dispersion and heterogeneity in TFP to be overstated. Following this approach erroneously attributes the variation of material inputs to productivity and resultantly ends up with a distorted image of the productivity distribution and consequently misleading policy implications ($cf.$ Section 5.1).

GNR propose a simple estimator for gross-output production functions with at least one flexible input. They establish identification by exploiting information in the first order condition with respect to the flexible input from the firm's static profit maximisation problem. This flexible approach controls for both the transmission and value-added bias discussed above. It

[7] Given that y_{it} is a variable reported in the data, we expect ε_{it} to also contain measurement error to output and prices. This is assumed to be symmetric across firms and thus does not affect our estimation.

[8] Firm specific prices, to the extent that they are exogenous, can potentially serve as instruments for flexible inputs and solve for the identification problem (Doraszelski and Jaumandreu 2013; De Loecker et al. 2016). However, in practice it is hard to find prices at the firm/plant level that reflect differences in expected rather than chosen prices (Griliches and Mairesse 1999; Ackerberg et al. 2007). Therefore, in most datasets, prices capture market power and input/output quality differences rendering them endogenous (Fox and Smeets 2011; Kugler and Verhoogen 2012; Atalay 2014).

imposes no specific functional form, nor does it rely on strong assumptions made in alternative proxy variable frameworks, e.g. the assumption of scalar unobservability to invert the proxy demand function (e.g. Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg et al. 2007, 2015). In line with most of the the proxy variable methods, the GNR procedure follows two-steps and allows us to both estimate production functions and identify the productivity effects from inter-industry offshoring and inshoring. Appendix A outlines the assumptions and steps followed.

Note that TFP is not identical to disembodied technological change, often referred to as the 'Solow Residual' (Solow 1957). Here TFP also includes the impact of inputs that are not explicitly measured (e.g. management and human capital skills). Further, our TFP estimates are revenue based as we do not observe physical output, but only monetary values which we deflate at the industry-country-year level. Results should be interpreted bearing this caveat in mind (Klette and Griliches 1996).

3.2 Effects of Inter-industry Offshoring and Inshoring on TFP

We now specify how we model the effects of inter-industry offshoring and inshoring on productivity as a learning process. We start with the two-stage specification that is typical to the literature and argue why it is misspecified. We then present the correctly specified one-stage procedure on which the severity of the value-added bias will be examined and inference will be based.

To analyse the inter-industry productivity effects of offshoring and inshoring we allow the relevant measures to shift the productivity path, ω_{it}. Typically, a two-stage approach would be taken for such a problem. In a first stage, a TFP estimate would be obtained using one of the techniques discussed above, to be followed by a second stage where TFP as a dependent variable is related to the variables of interest. A non-negligible part of the empirical literature employs a static specification in the second stage (henceforth 2S-Static), which in our case looks like:

$$\hat{\omega}_{it} = \rho_o + \rho_p proxies_{jct-1} + \rho_x X_{it-1} + \phi_t + \phi_j + \phi_c + \xi_{it} \tag{6}$$

where $proxies_{jct-1}$ is the vector of inter- and intra-industry offshoring and inshoring proxies, at the industry-country-level (jc); X_{it-1} is a vector of additional firm-level controls; ϕ_t, ϕ_j and ϕ_c are a set of dummies for time, industry and country fixed effects, respectively; and ξ_{it} is an i.i.d. error term.

When using specification (6) in the second stage, a conceptual gap with stage one emerges (Fernandes 2007). Stage one assumes a Markov process for productivity, while stage two uses a static specification. Stage two thus ignores the dynamic nature of productivity which results in serial correlation that can not be eliminated with fixed effects. As such, equation (6) is misspecified. The following dynamic specification (henceforth 2S-Dynamic) resolves this issue:[9]

$$\hat{\omega}_{it} = \rho_o + \rho_\omega \hat{\omega}_{it-1} + \rho_p proxies_{jct-1} + \rho_x X_{it-1} + \phi_t + \phi_j + \phi_c + \xi_{it} \tag{7}$$

However, the two-stage approach suffers from a second conceptual problem as formally derived by De Loecker (2013) and discussed in De Loecker and Goldberg (2014). In equation (7) current productivity—conditional on lagged productivity—depends on the lagged proxies and other determinants that are in the firm's information set when decisions are made. These inter-industry effects (and other determinants that possibly shift the productivity path) are not taken into account in the Markov process in the first-stage. To solve for this inconsistency, we introduce the relevant proxies and control variables in the law of motion and estimate them—as in Aw et al. (2008); Kasahara and Rodrigue (2008); Doraszelski and Jaumandreu (2013) and De Loecker (2013)—*within* the GNR procedure in (8).[10] Henceforth we refer to the estimation of (8) as 'One-Stage' (1S-Dynamic).

$$y_{it} = f_j(k_{it}, l_{it}, m_{it}) + \Big(\rho_o + \rho_\omega \omega_{it-1} + \rho_p proxies_{jct-1} + \rho_x X_{it-1} + \phi_t + \phi_j + \phi_c + \xi_{it}\Big) + \varepsilon_{it} \tag{8}$$

We use (8) to compare the recent GNR procedure to that of Ackerberg, Caves, and Frazer (2015) (henceforth ACF) which is widely popular. We explore the value-added bias by comparing our GNR estimates to those obtained when using the ACF method with a value-added production function as described in Appendix B. What is more, gross-output production functions with at least one flexible input are not identified under any of the traditional dynamic and semi-parametric estimation methods. Therefore, we also compare GNR with a gross-output production function using the ACF estimation procedure.[11] The latter estimation is computationally feasible, but it does not identify the true production function parameters.[12]

As opposed to ACF, the GNR framework allows for a specification that controls for firm fixed effects.[13] GNR indicate that allowing for fixed effects does not bear an important impact on the estimated output elasticities of the production function. However, as our main interest lies with the estimation of the impact of the proxies on productivity we control for firm fixed effects (ϕ_i) in (8) to correct for the potential presence of dynamic panel bias (Nickell 1981). In addition, we control for unobserved factors that could be driving growth performance at the

[9]In the case of firm fixed effects the estimation of the following specification is inconsistent (Nickell 1981). To solve for the endogeneity induced by the correlation between the persistence term and the unobserved firm fixed effects, Fernandes (2007) and Topalova and Khandelwal (2011) apply an Arellano and Bond (1991) approach. However, this is also inconsistent since the presence of firm fixed effects violates the assumption of scalar unobservability required in the first stage to invert out the proxy demand function (Ackerberg et al. 2007).

[10]A direct approach where the variables of interest are incorporated in the first-step's control function (e.g. Fernandes 2007; Topalova and Khandelwal 2011) is problematic since it ignores the dynamic nature of TFP and just provides an equilibrium relationship between TFP and the variables of interest, rather than a learning process framework which is pertinent to us. In practice, incorporation in the control function only helps to control for unobserved differences, e.g. price changes, induced from the relevant shocks.

[11]The procedure follows from Appendix B but with a gross-output production function.

[12]See Bond and Söderbom (2005) for an exposition under a Cobb-Douglass specification.

[13]For a detailed description, see Appendix O5-1 of their paper. For an overview, see Appendix A.3 of this paper.

industry (ψ_j) or country (ψ_c) level (see section 3.3 on how we incorporate these factors in our estimation procedure). Therefore, (9) will be our preferred specification upon which economic inference will be made (henceforth 1S-D-FFE).

$$y_{it} = f_j(k_{it}, l_{it}, m_{it}) + \Big(\rho_o + \rho_\omega \omega_{it-1} + \rho_p proxies_{jct-1} + \rho_x X_{it-1} + \phi_t + \phi_i + \psi_j + \psi_c + \xi_{it}\Big) + \varepsilon_{it} \tag{9}$$

3.3 Estimation

Because proxies are industry-country-year specific, we pool firms across all manufacturing industries and European countries in the data to maintain sufficient variation. For the production technology we rely on a Cobb-Douglas functional form: $f_j(\cdot) = \sum_v \alpha_v^j v_{it}$, where $v = \{k, l, m\}$ refers to a gross-output and $v = \{k, l\}$ to a value-added production function. On the one hand, this specification is the simplest and most commonly used in the literature, albeit at the expense of restricting the elasticities of substitution between inputs to unity. On the other hand, given the parameter space and data constraints in mind, its simplicity allows us to control for additional dimensions, i.e. growth differentials in production technologies across industries (j), without depleting the degrees of freedom and impeding the estimation routine.[14]

In the first stage of specifications (6)-(7), following the seminal work of Olley and Pakes (1996), we assume an exogenous first order Markov process where current productivity is a (linear) function of lagged productivity plus an i.i.d. error term which captures innovations to productivity. More specifically: $\omega_{it} = \rho_o + \rho_\omega \omega_{it-1} + \phi_j + \xi_{it}$. Note that since the production function is industry specific (j) and mean productivity (ρ_o) cannot be separately identified from the constant of the production function, it is imperative to use industry fixed effects (ϕ_j) in order to normalize $f_j(\cdot)$ to contain no constant.

For specifications (6)-(8) we use time ϕ_t, industry ϕ_j and country ϕ_c fixed effects to account for macroeconomic shocks and aggregate structural differences at the industry and country level, respectively. The above equations can consistently be estimated with a least-squares dummy variables (LSDV) regression since the number of industries and countries is small compared to the panel dimension. In specification (9), firm fixed effects ϕ_i account for unobserved time invariant firm characteristics which render a LSDV regression estimation inconsistent (Nickell 1981). Following the dynamic panel literature, the GNR estimation procedure can be easily augmented to accommodate for firm fixed effects by differencing them out in the second step and instrumenting the (now endogenous first-differenced) persistence component with lagged levels à la Arellano and Bond (1991) (see Appendix A.3).[15] Note that in the first-differenced

[14] Alternatively, one could allow for more flexible substitution patterns between inputs, i.e. translog functional form, and/or production technologies that vary both across industries and countries. However, such choices come with typical trade-offs faced by empirical researchers: increased parameter space; insufficient number of observations for certain country-industry pairs; and computationally intensive estimation routines.

[15] As shown by Blundell and Bond (1998), first differencing in a dynamic panel setup performs poorly when ω_{it} is close to a random walk. Therefore, a "System GMM" approach can alternatively be applied.

equation of the second step, we also add industry ϕ_j and country ϕ_c fixed effects to account for unobserved factors that could be driving growth performance at the industry (ψ_j) or country (ψ_c) level, respectively.

The estimation procedures described above, contain multiple steps and/or stages and as such closed form solutions for the variance-covariance matrices are not apparent. Therefore, for the statistical inference of our estimates, we obtain standard errors by using the nonparametric bootstrap method (see Efron 1979, 1982; Horowitz 2001; Davidson and MacKinnon 2004). More specifically, we randomly draw with replacement the whole firm (not observations) from the original sample and generate B=199 bootstrapped samples. Bootstrap samples are taken independently within each strata, i.e. industry. For each parameter estimate from the original sample $\hat{\theta}$, $\hat{\theta}_k$ is the estimate from the k^{th} bootstrap replication and $\bar{\theta}$ is the mean of the $\hat{\theta}_k$s. As such, the bootstrap standard error can be written as:

$$se(\hat{\theta}) = \left(\frac{1}{B-1} \sum_{k=1}^{B} (\hat{\theta}_k - \bar{\theta})^2 \right)^{1/2} \tag{10}$$

The computed standard errors can be used for statistical inference similar to any other asymptotically valid standard errors.

3.4 Endogeneity

Endogeneity issues should be less of a concern given that our focus centers on inter-industry effects where productivity shocks are transmitted through relevant linkages with firms in upstream or downstream industries. However, to further alleviate possible endogeneity concerns, we discuss the relevant steps followed.

First, a given firm might have some impact on the offshoring and inshoring choice of its client or supplier industries through affiliated firms in these industries. This would render our proxies endogenous for sufficiently granular firms. Therefore, for the additional firm-level controls X_{it-1}, we construct two dummy variables to indicate whether the firm owns any domestic subsidiaries or is owned by any other domestic firm. Using these variables in conjunction with the multinational status of a firm (i.e. whether it has a foreign shareholder or a foreign subsidiary), we control for any type of domestic demand or supply chain relationship between parent and affiliate firms.

Second, we assume that the activity of upstream or downstream firms is not immediately observed. It is gradually explored by the firm, resulting in a delay in the transmission of productivity effects. We use one year lagged proxies to capture such sluggishness. Simultaneity bias is less of a concern, given that current firm-level TFP is unlikely to affect lagged values of inter-industry offshoring and inshoring. Intra-industry offshoring and inshoring are expected to contemporaneously affect firm productivity, which is consistent with the timing assumption for material inputs used in estimating TFP. This is because material inputs are assumed to be flexible. In this case, the decision to offshore or inshore is endogenous and should be modelled accordingly.[16]

Third, in specification (9) upon which inference will be made, similar to the persistent term, we also instrument with deeper lagged levels ($t-2$) of both the proxies ($proxies_{jct-1}$) and the rest of the controls (X_{it-1}) in the first-differenced model. Deeper lagged levels control for cases where regressors are correlated with the effects, e.g. the white-noise measurement error model in which mismeasured regressors are correlated with contemporaneous errors but not with lagged or future errors. On top of the firm fixed effects we also control for unobserved factors that could be driving growth performance at the industry (ψ_j) or country (ψ_c) level and thus would render the estimation inconsistent if not controlled for.

Finally, in the results section, we provide a series of robustness checks that allow us to exclude the presence of specification biases which could arise if our modeling assumptions made during the estimation of specification (9) were incorrect.

4 Data

We construct a firm-level panel of manufacturing firms in 19 EU countries[17] from 2000 to 2014 from the Amadeus database by Bureau van Dijk Electronic Publishing (2018) (BvDEP). BvDEP regularly updates the information set in Amadeus and releases a monthly version which contains the latest information on ownership. Firms that exit the market are dropped fairly rapidly. For a complete set of financial and ownership information over time, we use a time series of (annual) releases to construct a consistent database. This allows us to build a dataset with nearly full financial and administrative information, i.e. balance sheet, profit and loss account activities, location, ownership, exit and entry. Merlevede et al. (2015) describe the construction and representativeness of the data at length.

We focus on the sample of active[18] firms that file unconsolidated accounts.[19] We retain firms which report their sales, tangible fixed assets, number of employees, material costs, ownership information and NACE 2-digit industry classification.[20] Following Merlevede et al. (2015), for better coverage and representativeness across EU countries, we keep firms with more than 20 employees on average. We also drop firms if either value-added or output is missing to have the same sample size when comparing gross-output and value-added production function estimates.

[16]See Amiti and Wei (2005); Görg et al. (2008); Michel and Rycx (2014) and Halpern et al. (2015).

[17]Austria (AT); Belgium (BE); Bulgaria (BG); Croatia (HR); Czech Republic (CZ); Estonia (EE); Finland (FI); France (FR); Germany (DE); Hungary (HU); Italy (IT); Norway (NO); Poland (PL); Portugal (PT); Romania (RO); Slovakia (SK); Slovenia (SI); Spain (ES); and Sweden (SE).

[18]We exclude firms that are dissolved, in liquidation, inactive and in bankruptcy since their assets can genuinely go down to (almost) zero.

[19]This refers to accounts not integrating the statements of possible controlled subsidiaries or branches of the concerned company. This avoids double counting at the firm level but is uninformative about the plant dimension.

[20]Appendix Table D.1 provides an overview of the NACE Rev.2 2-digit industries included (Eurostat 2018a).

Lastly, we remove outliers using the BACON method proposed by Billor et al. (2000).[21] This results in an unbalanced panel of 169,387 manufacturing firms and 1,298,809 observations across the 19 EU countries in our dataset for the period 2000-2014 (see Table 1).

Table 1: Summary Statistics

Firm-level	Obs.	Mean	St.Dev.	p25	p50	p75
Sales†	1,298,809	32,891	250,498	2,482	6,188	17,317
Tang. Fixed Assets†	1,298,809	7,479	80,609	3,02	1,060	3,581
Material Inputs†	1,298,809	19,865	195,238	968	2,862	9,008
Number of Employees	1,298,809	126	367	29	48	106
SUB^{dom}	1,298,809	.048	.21	0	0	0
SUB^{for}	1,298,809	.043	.2	0	0	0
SHH^{dom}	1,298,809	.21	.41	0	0	0
SHH^{for}	1,298,809	.096	.29	0	0	0
Industry-level						
$OFFdown$	5,275	0.289	0.098	0.220	0.278	0.343
$INup$	5,275	0.248	0.085	0.183	0.243	0.302
$OFFup$	5,275	0.263	0.075	0.209	0.252	0.307
$INdown$	5,275	0.305	0.130	0.209	0.300	0.390
OFF	5,275	0.386	0.162	0.265	0.368	0.486
IN	5,275	0.459	0.263	0.242	0.445	0.671

Notes: † Monetary variables in thousands of Euro. Unbalanced panel of 169,387 firms in 19 manufacturing industries across 19 EU countries over the period 2000-2014.

Monetary variables are deflated using the appropriate country-specific NACE 2-digit output deflator from the EU KLEMS database (EU KLEMS 2017). Real output (Y) is sales deflated with producer price indices. Capital (K) is tangible fixed assets deflated by the average of the deflators of various NACE 2-digit industries (Javorcik 2004).[22] Real material inputs (M) is material inputs deflated by an intermediate input deflator constructed as a weighted average of output deflators, where country-time-industry specific weights are based on intermediate input uses retrieved from IO-tables. Labour (L) is the number of employees. Finally, SUB^{dom} and SUB^{for} are dummy variables indicating whether the firm controls more than 10% of the shares of a domestic or foreign firm, respectively. SHH^{dom} and SHH^{for} are dummy variables indicating whether more than 10% of the firm's shares are owned by a domestic or foreign firm, respectively.

For the measurement of proxies we use the WIOD November 2016 Release (henceforth WIOD), which provides a time series of World IO Tables (WIOT) for 43 countries worldwide

[21]BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital, and material and material's revenue share. We first trim at the industry and then manufacturing level.

[22]Office machinery and computing (26); electrical machinery and apparatus (27); machinery and equipment (28); motor vehicles, trailers, and semi-trailers (29); and other transport equipment (30).

and a table covering the rest of the world for the years 2000-2014.[23] WIOD uses the Statistical classification of products by activity (CPA) which contains 56 industries, 19 out of which are in the manufacturing sector.[24] A major advantage over other databases is that the WIOT varies over time and that information on imports of goods does not rely on the standard proportionality assumption. Instead, a more flexible approach is followed whereby import proportions vary over end-use categories. This provides greater variability over time and intermediate input types. This extra level of detail is expected to unmask possible heterogeneity and provide better identification. The bottom panel of Table 1 presents summary statistics for the firm and industry-level variables in our sample.

5 Results

In this section we first assess the importance of misspecification biases that are frequent in the literature and the impact of value-added bias on the estimated productivity effects of inter-industry offshoring and inshoring. We then analyse the productivity effects of inter-industry offshoring and inshoring in detail.

5.1 Misspecification and Value-added Bias

Misspecification.—Notwithstanding that it is misspecified, we begin with specification (6) in column 1 (2S-Static) because of its frequent use in the empirical literature. The sign, magnitude and significance of the coefficients are not entirely consistent with those in the third column (1S-Dynamic) based on the correctly specified specification (8), leading to distorted inference. Therefore, it is crucial to at least control for the dynamic nature of productivity. Results using specification (7) in the second column (2S-Dynamic) control for this bias but fail to correctly specify the learning process in the first step (De Loecker 2013). Comparing columns 2 and 3 we observe large differences in estimated coefficients. As such, for multi-step empirical methodologies it is key to use specifications that are internally consistent with the assumptions across steps.

Value-added Bias.—To explore the extent of the value-added bias, we estimate productivity using the ACF two-step procedure with a value-added production function. In Figure 4, we plot the re-centered (at the industry level) distributions of estimated TFPs using the GNR gross-output and the ACF value-added (along with the ACF gross-output which is only discussed in the following sub-section). A visual inspection suggests that the latter generates a more heterogeneous and dispersed distribution of TFP estimates, indicating that the value-added bias can lead to distorted estimates.[25] In column 4 of Table 2 we therefore re-estimate column 3

[23] See Timmer et al. (2015, 2016) for a detailed description of the construction of the tables.

[24] See Table D.1 in Appendix D for correspondence with NACE Rev.2 2-digit.

[25] Under the same rationale, in Figure D.3 in Appendix D, we plot the re-centered (at the industry level)

based on the ACF estimation procedure under a value-added production function. It is clear from column 4 that the correctly specified one-stage procedure for ACF value-added produces point estimates that differ in terms of magnitude compared to column 3. This is likely driven by the presence of value-added bias (see Appendix C for an exposition of the bias).

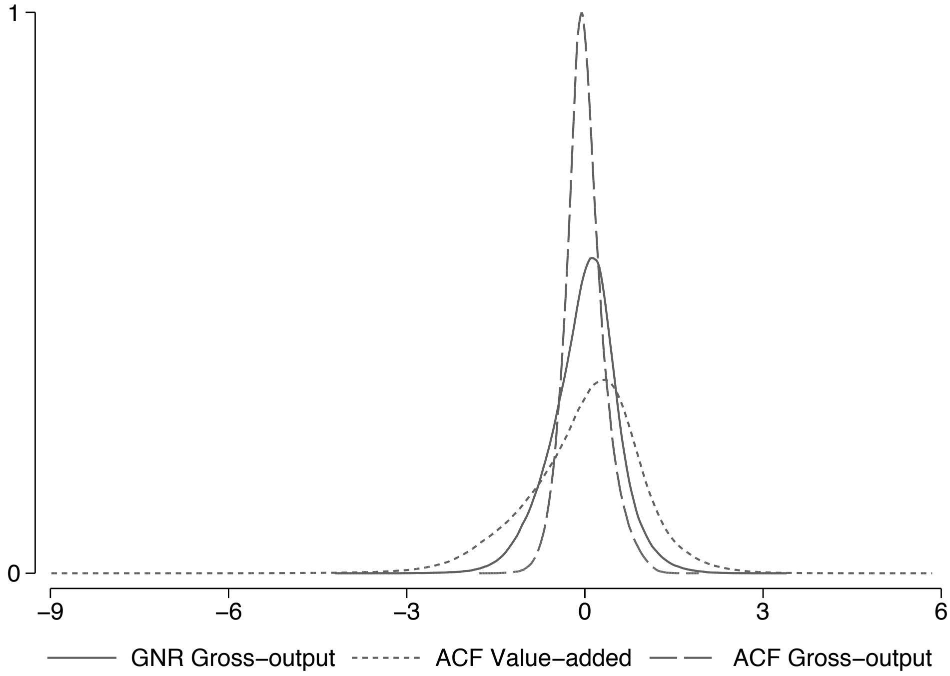
Table 2: TFP effects from inter-industry offshoring and inshoring for various empirical specifications

	(1)	(2)	(3)	(4)	(5)
	GNR Gross-output			ACF Value-added	ACF Gross-output
	2S-Static	2S-Dynamic	1S-Dynamic	1S-Dynamic	1S-Dynamic
ω_{it-1}		0.865***	0.911***	0.899***	0.797***
		(0.003)	(0.002)	(0.002)	(0.004)
$OFFdown_{jct-1}$	-0.773***	0.104***	0.140***	0.131***	-0.006**
	(0.080)	(0.017)	(0.017)	(0.018)	(0.003)
$INup_{jct-1}$	0.204***	0.094***	0.129***	0.088***	-0.007***
	(0.061)	(0.009)	(0.009)	(0.011)	(0.002)
$OFFup_{jct-1}$	0.230***	-0.017	-0.067***	-0.038**	0.003
	(0.082)	(0.014)	(0.015)	(0.018)	(0.004)
$INdown_{jct-1}$	0.466***	0.028***	-0.013*	-0.007	0.009***
	(0.045)	(0.008)	(0.007)	(0.009)	(0.002)
OFF_{jct-1}	-0.112***	-0.011	-0.033***	-0.018**	0.008***
	(0.040)	(0.008)	(0.007)	(0.009)	(0.002)
IN_{jct-1}	-0.027	0.021***	0.032***	0.012***	-0.002***
	(0.018)	(0.003)	(0.003)	(0.004)	(0.001)
SHH^{dom}_{it-1}	0.115***	0.013***	0.014***	0.015***	-0.000**
	(0.012)	(0.001)	(0.001)	(0.001)	(0.000)
SUB^{dom}_{it-1}	0.044***	0.003**	0.002**	0.003***	-0.000
	(0.006)	(0.001)	(0.001)	(0.001)	(0.000)
SHH^{for}_{it-1}	0.207***	0.028***	0.029***	0.030***	-0.001***
	(0.018)	(0.001)	(0.001)	(0.001)	(0.000)
SUB^{for}_{it-1}	0.151***	0.024***	0.023***	0.025***	0.001***
	(0.012)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	1,040,851	1,040,851	1,040,851	1,040,851	1,040,851

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include year, industry and country fixed effects. In columns 1 and 2 standard errors are computed using the nonparametric bootstrap with 199 replications over the two-stage estimation procedure (with GNR two-step estimation procedure in the first stage) and are reported in parentheses below point estimates. In columns 3, 4 and 5 standard errors are computed using the nonparametric bootstrap with 199 replications over the one-stage dynamic GNR gross-output, ACF value-added and ACF gross-output estimation procedures, respectively, and are reported in parentheses below point estimates. Bootstrap samples are taken independently within each strata, i.e. industry.

distributions of the estimated TFPs for different ownership-linked firm-types using the GNR gross-output and the ACF value-added. As expected, the productivity distributions of ownership-linked firms visually dominates the respective distribution of non-ownership-linked firms (Helpman et al. 2004; Yeaple 2006). However, in the case of a value-added production function (right panel), this is more dominant compared to a gross-output function (left panel) pointing again to the presence of value-added bias.

Figure 4: Re-centered (at the industry level) distributions of estimated TFP ($\hat{\omega}_{it}$)



ACF Gross-output.—GNR prove that gross-output production functions with at least one flexible input are not identified under the ACF estimation method. We next proceed as if we are unaware of this result and erroneously estimate a gross-output production function using the ACF framework. Recall that the estimation is computationally feasible, but results in estimates of ω_{it} that misrepresent TFP. As shown in Figure 4, the TFP distribution using ACF gross-output is tighter but more similar to that under the GNR procedure. It seems that the value-added bias is 'controlled for' when employing a gross-output specification. In column 5 of Table 2 we re-estimate the specification from column 3 but now use the ACF estimation procedure under a gross-output production function. As can be seen, the correctly specified one-stage procedure in column 5 produces results that are neither in line with ACF under a value-added production function (column 4) nor with GNR under a gross-output production function (column 3). This highlights the non-identification issues in column 5 that lead to estimated coefficients having no structural interpretation. Overall, the findings in Table 2 emphasise the importance of correctly identifying gross-output production functions, as these identification issues potentially distort empirical results non-trivially.

5.2 TFP Effects from Inter-industry Offshoring and Inshoring

In Table 3 we first introduce our preferred baseline specification (9) (column 1) and then test the robustness of our findings for a number of alternative assumptions in the estimation procedure (columns 2-4), the construction of the variables (columns 5-6), and firm size (columns 7-8). Finally, we discuss some additional robustness tests.

Firm Fixed Effects.—Column 1 shows the baseline results of estimating (9) using the GNR procedure (1S-D-FFE). The obtained point estimates are fairly similar to those in column 3 of Table 2.[26] In terms of statistical significance, however, we observe more substantial differences. When accounting for firm-specific effects, only downstream offshoring and upstream inshoring remain significant at the 1% level, while the rest of the variables of interest lose all significance.

Table 3: TFP effects from inter-industry offshoring and inshoring under baseline specification and robustness to alternative assumptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Alternative Assumptions			Fix Weights in 2000		Size	
	1S-D-FFE	Country-Time FEs	Labour Timing	Imperfect Competition	All Proxies	$OFFdown$ & $INup$	Small	Medium & Large
ω_{it-1}	0.548***	0.445***	0.535***	0.539***	0.549***	0.546***	0.455***	0.571***
	(0.014)	(0.019)	(0.013)	(0.012)	(0.014)	(0.013)	(0.014)	(0.015)
$OFFdown_{jct-1}$	0.187***	-0.022	0.238***	0.178***	0.137**	0.111**	0.199***	0.143***
	(0.055)	(0.029)	(0.047)	(0.047)	(0.054)	(0.056)	(0.028)	(0.052)
$INup_{jct-1}$	0.147***	0.075**	0.163***	0.297***	0.181***	0.163***	0.110***	0.157***
	(0.044)	(0.032)	(0.052)	(0.045)	(0.055)	(0.053)	(0.025)	(0.048)
$OFFup_{jct-1}$	-0.035	-0.027	-0.042	-0.630***	-0.047	0.030	0.032	-0.098*
	(0.044)	(0.033)	(0.045)	(0.050)	(0.043)	(0.048)	(0.031)	(0.052)
$INdown_{jct-1}$	0.009	0.053*	0.038	-0.039	0.012	0.041	-0.005	-0.012
	(0.054)	(0.029)	(0.037)	(0.054)	(0.037)	(0.043)	(0.019)	(0.054)
Observations	845,383	845,383	845,383	845,383	845,383	845,383	353,687	491,696

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include intra-industry offshoring and inshoring, dummies for domestic and foreign ownership links ($SHH^{dom}, SUB^{dom}, SHH^{for}, SUB^{for}$), and year, industry and country fixed effects. Column 2 also includes additive country-year fixed effects. Standard errors are computed using the nonparametric bootstrap with 199 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates. Bootstrap samples are taken independently within each strata, i.e. industry.

Alternative Assumptions.—To exclude the possibility that country specific growth trends are driving our results, we augment the baseline specification with country-time fixed effects (column 2). We find that downstream offshoring becomes negative and insignificant while only upstream inshoring remains significant (at the 5% level) but with its magnitude halved.[27]

So far we have assumed that rigidities in the European labour market prevent the adjustment of labour within the (accounting) year. This translates to a one period lag between the choice of labour and its realisation in the production process (hence in the accounting data). Therefore, labour, as in the case of capital, is predetermined in period t. In column 3 we relax this assumption. Specifically, we now assume that the European labour market is more flexible but still subject to adjustment costs. In this case, labour is chosen during the realisation of productivity, i.e. between $t-1$ and t and thus correlated with the error term. To guarantee identification in the second step of the GNR procedure, we use l_{it-2} instead of l_{it-1} in the orthogonality conditions

[26] For lagged productivity, we find an expected decrease in the point estimate since we now control for the upward bias originating from the positive correlation between the persistence term and firm fixed effects (Arellano 2003).

[27] Computationally it is an extremely time consuming estimation and thus we avoid from using it as our baseline.

of the first differenced equation. Under such alternative timing assumptions, results remain with higher magnitudes.

In column 4 we account for differences in prices in the output market. To control for unobserved variation in firm-specific prices we introduce more structure and assumptions (such as a time-varying iso-elastic CES demand system coupled with monopolistic competition similar to Klette and Griliches (1996) and De Loecker (2011)), following the methodology proposed by GNR. An exact description of the estimation procedure can be found in Appendix O5-4 of GNR. On top of the estimated effects of interest, we are also able to identify aggregate time-varying markups (see Figure D.4 in Appendix D).[28] This is expected to be insightful to the extent to which, on average, firms adjust their markups over time. However, for any deviation from this assumption we would need more detailed data, e.g. firm-level output prices, which is not currently available for such an extensive cross-country dataset. Therefore, as far as our approach accounts for price differences in the output market, the effects presented in column 4 remain similar to the baseline in column 1, with the exception of upstream offshoring which is now highly significant.

Construction of Variables.—To test robustness of the weights used to build our proxies of interest, we fix weights to their values at 2000, the start year of the sample, to eliminate potential distortions due to differences in the evolution of offshoring or inshoring across time, countries and industries. Specifically, since these weights refer to domestic transactions, they could potentially be affected over time by the offshoring/inshoring behaviour of the linked industries. In column 5 we fix the weights for all proxies while in column 6 we fix the weights for downstream offshoring and upstream inshoring only. This is because downstream offshoring and upstream inshoring measures are more likely to be directly affected, i.e. the decision to source or supply domestically could be affected by the intensity of offshoring or inshoring, respectively. Earlier findings are confirmed, with upstream inshoring reported as highly significant, and downstream offshoring also significant but less robust. Therefore, our result does not seem to be driven by the choice of a specific weighting scheme.

Given the relatively high level of aggregation in the measures of interest, we find a moderate to high correlation between the proxies (see Table D.2 in Appendx D). To avoid potential issues from multicollinearity, we re-estimate the baseline specification by introducing each inter-industry proxy separately both when intra-industry proxies are included and excluded. We find that the main result does not appear to be driven by the presence of multicollinearity in the proxies (see columns 2-10 from Table D.3 in Appendix D).

Firm Size.—In columns 7 and 8 we split our sample into small and medium-large firms based on European Commission guidelines.[29] On the one hand, this cut-off splits the sample in

[28] One can also allow markups to vary across countries and time by assuming a CES demand system with country-time-varying elasticity of demand.

[29] Small firms report on average less than 50 employees and up to ten million Euro turnover while medium-large firms are the ones above this cut-off (European Commission 2018).

two since 99% of European firms are small and medium-sized (European Commission 2018). On the other hand, we choose this cut-off since it is important for access to finance and EU support programmes targeted specifically at these firms. Overall, this specific cut-off ensures that we observe both small and medium-large firms in all industries considered. We find that both small and medium-large firms are subject to the same effects as in the baseline case. In other words, medium-large firms do not seem to be affected differentially by upstream inshoring.[30] This may reflect the fact that dimensions other than size determine the extent to which firms are exposed to the effects of internationalisation through the domestic supply chain.

Additionally, Amiti et al. (2016) find that small firms do not exhibit strategic complementarities in price setting. Instead, they fully pass through shocks to their marginal costs to their prices. In contrast, large firms exhibit strong strategic complementarities and incomplete pass-through. Therefore, to the extent that strategic complementarities and incomplete pass-through could be driving our results, we might expect differential effects between small and large firms. This hypothesis is not supported by our results, however.[31]

Additional Robustness.—To further support the validity of our results we proceed with a battery of additional robustness checks which are presented in columns 3-6 in Table D.4 of Appendix D. In column 3, instead of deeper lags in levels, we now use the first-differenced values to instrument for the variables of interest $proxies_{jct-1}$ and additional controls X_{it-1}, i.e. treating them as exogenous. In column 4, we relax the threshold for dropping outliers from the 30$^{\text{th}}$ to the 15$^{\text{th}}$ percentile of the distribution of nominated outliers using the BACON procedure.[32] In columns 5 and 6 we bootstrap the baseline specification for 999 replications and without imposing a strata structure, respectively. In all of the above cases, results are robust.

Our overall conclusion from Table 3 and the additional robustness checks is that upstream inshoring appears to be the only robust channel for inter-industry effects of offshoring and inshoring on productivity. While the impact of downstream offshoring is significant in most specifications, the effect disappears when we control for country-time fixed effects. Therefore, domestic sourcing from industries that also export intermediates seems to be associated with higher productivity levels for a given firm. This effect is likely to originate from the firm's access to better intermediates, since they are also exported. However, this does not need to be the only mechanism since our results capture any potential learning process arising from this relationship, e.g. organisational practices, export network, etc. On the basis of the point estimate in column 1, a one standard deviation increase in upstream inshoring is associated with an increase in productivity of 1.13% in the short run and 2.50% in the long run.[33]

[30] For completeness, instead of splitting the sample, we estimate the empirical model by interacting the variables of interest with a dummy which takes values of one when a firm is small and zero otherwise. Results presented in column 2 of Table D.4 reveal that the difference in TFP effects from upstream inshoring between small and medium-large firms is not statistically significant.

[31] We have also experimented with keeping only large firms in the reference group. Results remain and are available upon request.

[32] This results in an additional 6,077 firms and 55,098 observations.

[33] The long-run effect is computed using estimates from column 1 of Table 3 based on the following formula:

5.3 Heterogeneity

Our results for firm size raise the question as to whether the effects of indirect internationalisation through domestic supply chain participation are specifically applicable to firms that do not (or are less likely to) directly participate in international or domestic supply chains. We test this in Table 4. To facilitate comparison between this exercise and our baseline, the first column of Table 4 repeats our baseline result (column 1 from Table 3). The results in columns 2-7 are also obtained from a 1-S-D-FFE estimation. To explore heterogeneity, we test for differential effects by interacting our proxies with a dummy variable D that is equal to one when a firm belongs to the group defined at the top of each column and zero otherwise.[34]

Table 4: Heterogeneity in TFP effects from inter-industry offshoring and inshoring

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		D=1 if a firm belongs to the group described below and 0 otherwise					
	Baseline	Domestic Links	Relatively Downstream	Relatively Low-tech	Labour Intensive	Downstream & Low-tech	Downstream & Labour-int
$OFFdown_{jct-1}$	0.187***	0.235***	0.262***	0.263***	0.222***	0.268***	0.216***
	(0.055)	(0.062)	(0.046)	(0.043)	(0.049)	(0.045)	(0.052)
$INup_{jct-1}$	0.147***	0.111**	0.004	0.067*	0.098***	0.049	0.051*
	(0.044)	(0.043)	(0.034)	(0.039)	(0.035)	(0.033)	(0.031)
$OFFup_{jct-1}$	-0.035	0.098*	0.004	0.004	0.024	-0.025	0.014
	(0.044)	(0.053)	(0.035)	(0.033)	(0.038)	(0.036)	(0.041)
$INdown_{jct-1}$	0.009	-0.065	-0.053	-0.033	-0.044	-0.030	-0.019
	(0.054)	(0.057)	(0.043)	(0.048)	(0.052)	(0.048)	(0.052)
$D*OFFdown_{jct-1}$		-0.039	-0.056	-0.134**	0.012	-0.035	0.010
		(0.046)	(0.049)	(0.063)	(0.039)	(0.065)	(0.063)
$D*INup_{jct-1}$		0.088**	0.355***	0.215***	0.129***	0.376***	0.315***
		(0.037)	(0.059)	(0.051)	(0.048)	(0.046)	(0.052)
$D*OFFup_{jct-1}$		-0.167***	-0.164***	-0.071	-0.223***	-0.319***	-0.329***
		(0.048)	(0.052)	(0.060)	(0.038)	(0.060)	(0.057)
$D*INdown_{jct-1}$		0.066	0.036	0.061*	0.087**	0.018	-0.017
		(0.042)	(0.031)	(0.032)	(0.042)	(0.033)	(0.034)
Observations	845,383	845,383	845,383	845,383	845,383	845,383	845,383

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include intra-industry offshoring and inshoring, dummies for domestic and foreign ownership links ($SHH^{dom}, SUB^{dom}, SHH^{for}, SUB^{for}$), and year, industry and country fixed effects. D is a dummy variable equal to one when firms are in the group category described in each column and zero otherwise. Standard errors are computed using the nonparametric bootstrap with 199 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates. Bootstrap samples are taken independently within each strata, i.e. industry.

Local Supply Chain Participation.—Purely foreign owned firms are more likely to be directly involved in an international supply chain relative to local standalone firms with no foreign ownership links that are more likely to depend on domestic clients and suppliers.

$INup_{jct-1}/(1-\rho_{\omega}) * sd(INup_{jct-1}) * 100$, where $INup_{jct-1}$ is the estimated short-run effect of upstream inshoring on TFP as specified in equation (9), ρ_{ω} is the persistence of TFP, and $sd(INup_{jct})$ is one standard deviation of the measure of upstream inshoring.

[34]Table D.5 in Appendix D repeats the analysis but with sample splits instead of dummy interactions.

Therefore, we may expect firms with no foreign ownership links to be more prone to inter-industry productivity effects relative to purely foreign owned firms. The interaction term in column 2 reveals that a significantly larger TFP effect can be detected from upstream inshoring for the group of firms that have no foreign ownership links throughout the entire sample period ($D = 1$). This suggests that the domestic supply chain may act as a vehicle for internationalisation effects through upstream inshoring.

Supply Chain Position.—Fally (2012) finds a large shift of value-added towards final stages of production, i.e. relatively downstream. He further shows that richer countries have a comparative advantage in goods that involve fewer production stages and goods that are closer to final demand.[35] This is also in line with Antràs et al. (2012), who show that a better rule of law, strong financial development, and relative skill intensity abundance are correlated with a higher propensity to export in relatively more downstream industries. This translates to the fact that relatively downstream industries both sell domestically and export output for final use more intensively. Therefore, relatively less output is expected to 'be left' for domestic supply in relatively downstream industries. Conversely, relatively downstream industries will have more upstream opportunities, i.e. relatively more output sourced from upstream, compared to relatively upstream industries.

As a result, more domestic upstream relationships will be generated in relatively downstream industries. This leads us to expect a larger potential for upstream inshoring in relatively downstream industries.[36] To account for possible heterogeneity in the absorption of learning effects from inter-industry linkages, we generate an industry-level measure of relative supply chain position as in Fally (2012) and Antràs et al. (2012) using WIOT. This measure of upstreamness gives the average 'distance' of each industry from final use. We rank industries as relatively downstream or upstream based on the median value of the distribution of this measure (see Table D.6 in Appendix D).[37]

Column 3 in Table 4 presents results when interacting the proxies with a dummy that is equal to one for the firms in relatively downstream industries and zero otherwise, i.e. relatively upstream. The expected heterogeneity of results between industries with different supply chain positions is confirmed. Firms in relatively downstream industries experience significantly larger productivity effects from upstream inshoring which appear as non-existent for relatively upstream industries.

[35] The latter stylised fact is consistent with the theoretical predictions of Costinot et al. (2013).

[36] Theoretical predictions of Antràs and Chor (2013) show that the incentive to integrate suppliers varies systematically with the relative position at which the supplier enters the production line. The nature of the relationship between integration and downstreamness depends crucially on the elasticity of demand faced by the final good producer and the degree of complementarity between inputs in production. However, for the case of the 19 European countries in our analysis we are not aware of any such elasticities and therefore we do not have any expectations for the exact direction of results. However, we do expect that relatively upstream or downstream firms vary on the way they absorb the inter-industry effects as they vary on their integration intensities.

[37] Relatively downstream includes industries with CPA: 12; 22; 21; 17; 20; 6; 5; 19; and 18, and relatively upstream industries with CPA: 10; 23; 11; 13; 16; 7; 14; 8; 15; and 18. As in Antràs et al. (2012), we observe that primary and resource-extracting industries tend to be relatively upstream.

High-tech vs. Low-tech.—Fally (2012) also finds that R&D intensive industries have become relatively less fragmented over time. This complements the work of Acemoglu et al. (2007, 2010) who find that innovative industries rely less intensively on outsourcing. Therefore, we might expect relationship-specific learning that depends on links between firms through the exchange of intermediate inputs to be less limited in low-tech industries where such relationships are more prevalent. On the basis of information on technological intensity of industries available in Eurostat (2018b), we construct a dummy variable equal to one when firms are in relatively low-tech industries and zero otherwise.[38] In column 4 of Table 4 we interact the proxies with the dummy variable and find that firms in low-tech industries experience significantly larger productivity effects from upstream inshoring.

Labour vs Capital Intensive.—Antràs (2003) shows that there is a higher propensity to integrate in capital intensive industries. Therefore, labour intensive industries are expected to rely more on outsourcing and consequently experience stronger productivity effects from inter-industry offshoring and inshoring. In column 5 of Table 4 we therefore interact the proxies with a dummy variable equal to one when a firm is in a relatively labour intensive industry (labour-int) and zero otherwise (capital-int).[39] As expected, we find that on average firms in relatively labour intensive industries experience statistically larger productivity effects from upstream inshoring.

Combinations.—For additional heterogeneity, we also create new groups based on combinations of the previous categories. In columns 6 and 7 of Table 4, the dummy variable is now the intersection of downstream & low-tech industries and downstream & labour intensive industries, respectively. As before, we expect these groups to generate relatively more intermediate input based relationships than their reference groups ($D = 0$). In line with the previous results, we find significantly larger productivity effects from upstream inshoring for these groups.

6 Conclusion

A large literature has examined the relationship between export and import behaviour, on the one hand, and productivity, on the other. Yet, notwithstanding a substantial amount of research on the direct productivity effects of firms' or industries' offshoring behaviour, potential indirect or spillover productivity effects of internationalisation have received less attention. We analyse potential productivity effects for a given firm that are associated with the internationalisation

[38]Eurostat (2018b) groups manufacturing activities to 'high-technology,' 'medium high-technology,' 'medium low-technology' and 'low-technology' based on the R&D expenditure/value added of industries. We define as relatively low-tech the industries in the 'low-technology' group with CPA: 5; 6; 7; 8; 9; and 22. The rest of the manufacturing industries are considered as relatively high-tech.

[39]Labour intensity is computed using the firm-level variables for capital (K) and labour (L) from our dataset. Labour-int industries are defined based on values smaller than the median of the distribution of average capital to labour ratios for each industry across countries and over the period considered. Labour-int includes industries with CPA: 6; 13; 16; 17; 18; 19; 21; 22; and 23, and capital-int the rest of the manufacturing industries.

behaviour of other firms in the domestic economy. Since sharing new knowledge with related parties along the supply chain is more likely than sharing it with competitors, we focus on the effects of internationalisation by local clients and suppliers of a given firm. Local firms may then experience indirect productivity effects of internationalisation through participation in the domestic supply chain.

We define two direct and two indirect 'channels' of possible inter-industry productivity effects for a given firm. In terms of direct channels, a given firm's (1) local client may source its intermediates from abroad (*downstream offshoring*) or (2) local supplier may also export intermediates that the given firm sources (*upstream inshoring*). In terms of indirect channels, a given firm's (3) local client may export its output (*downstream inshoring*) or (4) local supplier may import intermediates itself (*upstream offshoring*).

We combine rich firm level data for manufacturing firms from 19 EU countries for the period 2000-2014 with I-O tables to investigate potential productivity effects along the supply chain driven by trade in intermediates in linked industries. I-O tables are used to construct industry-level proxies for inter-industry offshoring and inshoring intensities in each country.

Recent literature typically relies on proxy variable methods which attempt to solve for the endogeneity problem that arises from firms choosing inputs while knowing their TFP. Despite their popularity, proxy variable methods suffer from identification issues when the production function contains at least one flexible input, e.g. materials. To circumvent this problem, applied economists focus on value-added production functions. As a result TFP suffers from a 'value-added bias' which leads to overstated dispersion and heterogeneity. To be able to correctly identify a gross-output production function, we use the estimator proposed by GNR, that controls for both the endogeneity and value-added bias. Additionally, we point to a common specification bias in applied work when ignoring the dynamic nature of productivity.

Empirically, we model potential productivity effects from inter-industry offshoring and inshoring as a learning process. Within a production function system we allow past experience from inter-industry offshoring and inshoring to affect productivity. Therefore, productivity measurement is crucial to our analysis. One way to proceed is to rely on proxy variable methods which are common in the literature. Despite their popularity, such methods suffer from identification issues when the production function contains at least one flexible input. To circumvent this problem, proxy variable methods focus on the estimation of value-added production functions instead which leads to overstated dispersion and heterogeneity of TFP. As such, in order to correctly identify a gross-output production function, we use the estimator proposed by Gandhi, Navarro, and Rivers (2018). We compare TFP estimates when using this procedure with those which result from other proxy variable methods (prevalent in the literature). This comparison allows us to assess the importance of value-added bias. Additionally, we point to a common specification bias in applied work when ignoring the dynamic nature of productivity.

Our results can be summarised as follows. Upstream inshoring, i.e. the export of intermediates by a given firm's local suppliers, appears to be a robust channel of inter-industry productivity effects in the EU. Sourcing from industries that also export these intermediates is associated with higher productivity levels of a given firm. This effect likely stems from access to better intermediates that are also exported. On the basis of our preferred point estimate, a one standard deviation increase in upstream inshoring is associated with a productivity increase of 1.13% in the short run and 2.50% in the long run. In support of our result, we find these effects to be stronger for those firms and industries that are less likely to be directly internationally involved. The effect is more prominent for firms with non-foreign ownership status, and for firms in relatively downstream and/or low-tech and/or capital intensive industries. Further, we demonstrate and confirm important biases that arise from ignoring the dynamic nature of productivity and specifying a value-added rather than a gross-output production function. Failing to correct for these biases may thus result in false conclusions.

This paper provides novel evidence of a channel through which internationalisation can affect firms. Given the empirical nature of our analysis, we see rich potential for our findings to motivate theoretical models on firm heterogeneity, supply chains and trade. Theoretical applications of our work could improve our understanding of the exact mechanisms behind our empirical findings. Such models would allow us to generate counterfactual predictions about patterns of trade, production and productivity from changes in policies related to internationalisation.

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Appendices

A GNR Two-step Estimation Procedure

This section serves as an overview of the basic steps and assumptions of the GNR estimation procedure. For a detailed and complete description refer to GNR. For simplicity, we disregard the industry dimension. The estimation is directly extended by allowing the functional form of the production technology $f(\cdot)$ to also vary by industry j.

This case considers the classic environment of perfect competition in both input and output markets. Capital and labour are assumed to be predetermined inputs and therefore chosen one year prior to the realisation of productivity, ω_{it}, i.e. at $(t-1)$. The only flexible input in the specification is material, assumed to freely adjust in each period (variable) and have no dynamic implications (static).

Conditional on the state variables and other firm characteristics, a firm's static profit maximisation problem yields the first order condition with respect to the flexible input, material:

$$P_t^M = P_t \frac{\partial}{\partial M_t} F(K_{it}, L_{it}, M_{it}) \mathrm{e}^{\omega}_{it} \mathscr{E} \tag{A.1}$$

where P_t^M and P_t are the price of material and output respectively. Under perfect competition in input and output markets, they are constant across firms within the same industry but can vary across time. By the time firms make their annual decisions, ex-post shock ε_{it} is not in their information set. Hence, firms create expectations that are similar across firms, $\mathscr{E} = E(\mathrm{e}^{\varepsilon_{it}})$.[40] It is important to account and correct for this term since ignoring it, i.e. $\mathscr{E} = 1$, inherently implies that we move from the mean to the median central tendency of $\mathrm{e}^{\varepsilon_{it}}$ (see Goldberger 1968).

Combining (A.1) with (5) and re-arranging terms, we retrieve a share equation:

$$s_{it} = ln\Big(G(K_{it}, L_{it}, M_{it}) \Big) + ln\mathscr{E} - \varepsilon_{it} \tag{A.2}$$

where s_{it} is the log of the nominal share of material and $G(K_{it}, L_{it}, M_{it}) = \frac{\partial}{\partial m_{it}} lnf(k_{it}, l_{it}, m_{it})$ is the output elasticity of the flexible input, material. Note that the share equation is net of the productivity term ω_{it}, inducing the transmission bias.

A.1 Step One

A Non Linear Least Squares estimation of the share equation (A.2) is applied, with:

$$G(K_{it}, L_{it}, M_{it})\mathscr{E} = \sum_{v_k+v_l+v_m \le v} \tilde{\gamma}_{v_k,v_l,v_m} k_{it}^{v_k} l_{it}^{v_l} m_{it}^{v_m}, \; with \;\; v_k, v_l, v_m \ge 0 \tag{A.3}$$

[40] We inherently assume that the existence of any measurement error is symmetric across firms and thus does not affect our results.

approximated by a polynomial series estimator of order ν. This step identifies ε_{it} (hence $\mathscr{E}$), $\gamma = \tilde{\gamma}/\mathscr{E}$ and thus the output elasticities of the flexible input material $G(\cdot)$.

A.2 Step Two

By integrating up the output elasticity of the flexible input:

$$\int \frac{G(K_{it}, L_{it}, M_{it})}{M_{it}} dM_{it} = ln\Big(F(K_{it}, L_{it}, M_{it})\Big) + \mathscr{B}(K_{it}, L_{it}) \tag{A.4}$$

we identify the production function up to an unknown constant of integration. By differencing it with the production function (5) we retrieve the following equation for productivity:

$$\omega_{it} = \mathscr{Y}_{it} + \mathscr{B}(K_{it}, L_{it}) \tag{A.5}$$

where $\mathscr{Y}_{it}$ is the log of the expected output net of the computed integral (A.4) and $\mathscr{B}(K_{it}, L_{it})$ is the constant of integration, approximated by a polynomial series estimator of degree ν:

$$\mathscr{B}(K_{it}, L_{it}) = \sum_{\nu_k + \nu_l \leq \nu} \alpha_{\nu_k, \nu_l} k_{it}^{\nu_k} l_{it}^{\nu_l}, \ with \ \ \nu_k, \nu_l > 0 \tag{A.6}$$

To proceed we exploit the assumption over the law of motion for productivity:

$$\omega_{it} = \rho_\omega \omega_{it-1} + \rho_z z_{it-1} + \xi_{it} \tag{A.7}$$

where lagged variables z_{it-1}, such as our measures of interest, are also allowed to affect current productivity outcomes.[41] We can now express the innovation of productivity, ξ_{it}, as a function of the parameters of the constant of integral to be estimated $\xi_{it}(\alpha)$, by regressing $\omega_{it}(\alpha)$ on $\omega_{it-1}(\alpha)$ and z_{it-1}.

This step proceeds with an iterative Generalised Method of Moments (GMM). The GMM citerion function is formulated using the following moment conditions: $E\left[\mathscr{Z}_\nu{}' \xi_{it}(\alpha)\right] = 0$, where $\mathscr{Z}_\nu = \left(k_{it}, l_{it}, \ldots, k_{it}^{\nu_k} l_{it}^{\nu_l}\right)$ is the 'instrument matrix' with its column space dimension depending on the degree ν of the polynomial used to approximate the constant of integration in (A.6). The choice of instruments is based on the timing assumption of inputs: capital and labour are predetermined inputs chosen at $t-1$ and thus orthogonal to the innovation of productivity. By minimising the sample analogue of the GMM criterion function, we retrieve estimates for the remaining parameters of the production technology (α) and also the Markov process parameters (ρ_ω and ρ_z).

For a polynomial of degree ν for both (A.3) and (A.6) the estimated gross-output production

[41] Without loss of generality, we use a linear first-order Markov process in line with the empirical specifications in the main text. Alternatively, a more flexible functional form can be considered where: $\omega_{it} = g\left(\omega_{it-1}, z_{it-1}\right) + \xi_{it}$.

function is:

$$y_{it} = \left(\sum_{\nu_k+\nu_l+\nu_m \leq \nu} \gamma_{\nu_k,\nu_l,\nu_m} k_{it}^{\nu_k} l_{it}^{\nu_l} m_{it}^{\nu_m} \right) m_{it} + \sum_{\nu_k+\nu_l \leq \nu} \alpha_{\nu_k,\nu_l} k_{it}^{\nu_k} l_{it}^{\nu_l} + \omega_{it} + \varepsilon_{it} \tag{A.8}$$

Using the estimated parameters from this two-step procedure, i.e. γ from step one and α from step two, we can now compute productivity $\hat{\omega}_{it}$ and other relevant functionals, i.e output elasticities of inputs and returns to scale, using (A.8).

A.3 Step Two with Firm Fixed Effects

For the case of firm-level fixed effects ϕ_i, the production function can be written as:[42]

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \tilde{\omega}_{it} + \varepsilon_{it} \tag{A.9}$$

where $\tilde{\omega}_{it} \equiv \omega_{it} + \phi_i$. Since fixed effects enter log-additively, the first order condition of the firm in (A.1) and the share equation in (A.2) remain the same, with $\tilde{\omega}_{it}$ replacing ω_{it}. Therefore, the first step described in Appendix A.1 is exactly the same.

In the second step, the Markov process (A.7) is augmented to:

$$\omega_{it} = \rho_\omega \omega_{it-1} + \rho_z z_{it-1} + \phi_i + \xi_{it} \tag{A.10}$$

Following the dynamic panel literature, we eliminate the fixed effects by first-differencing the above equation:

$$\Delta\omega_{it} = \rho_\omega \Delta\omega_{it-1} + \rho_z \Delta z_{it-1} + \Delta\xi_{it} \tag{A.11}$$

where Δ is the first difference operator. However, the above equation suffers from endogeneity induced by the correlation between $\Delta\omega_{it-1}$ and $\Delta\xi_{it}$. To solve for this, we instrument with deeper lags $(t-2)$ in levels à la Arellano and Bond (1991). In addition, to alleviate potential endogeneity concerns for our variables of interest (z_{it-1}), we also instrument them with deeper lags. Therefore, we can now express the innovation of TFP, as a function of both the parameters of the constant of integral and also the parameters of the endogenous variables in the Markov process $\Delta\xi(\alpha, \rho_\omega, \rho_z)$ by partitioning the "endgoneous part" from the above regression (Frisch and Waugh 1933; Lovell 1963).

The remaining part of the procedure is the same as in Appendix A.2 with the only difference being in the instrument matrix used to form the moment conditions $E\left[\mathscr{Z}_\nu{}' \Delta\xi(\alpha, \rho_\omega, \rho_z)\right] = 0$. In this case, $\mathscr{Z}_\nu = \left(k_{it-1}, l_{it-1}, \ldots, k_{it-1}^{\nu_k} l_{it-1}^{\nu_l}, \mathscr{Y}_{it-2}, z_{it-2}\right)$. The two last instruments are orthogonal to $\Delta\xi_{it}$ and thus identify ρ_ω and ρ_z, respectively.

[42] For a detailed description see Appendix C in GNR.

B ACF Two-step Estimation Procedure

This section provides an overview of the basic steps and assumptions in the ACF estimation procedure. For a detailed and complete description refer to ACF. This procedure controls for collinearity problems encountered in Levinsohn and Petrin (2003). Assumptions imposed about competition and timing of firms' decisions are as in the previous section. The only difference is that we now use a value-added production function, $VA_{it} = Y_{it} - M_{it} = F(K_{it}, L_{it})\mathrm{e}^{\omega_{it}}$, which in logs is expressed as:

$$va_{it} = f(k_{it}, l_{it}) + \omega_{it} + \varepsilon_{it} \tag{B.1}$$

where va_{it} is the log of double deflated value-added for firm i at time t.

Conditional on the state variables and other firm characteristics, firm's static profit maximisation yields material input demand $m_{it} = m(k_{it}, l_{it}, m_{it})$. To control for unobserved productivity, ω_{it}, we use the inverted intermediate input demand $\omega_{it} = m^{-1}(k_{it}, l_{it}, m_{it})$ under the assumption of monotonocity of m in ω.[43] Alternatively, we can rewrite (B.1) as:

$$va_{it} = \phi(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \tag{B.2}$$

B.1 Step One

For a polynomial approximation of order κ for $\phi(\cdot)$, an Ordinary Least Squares (OLS) regression on (B.2) delivers a measure of output purged from ex-post shocks and measurement error in output, $\hat{\phi}_{it}$.[44]

B.2 Step Two

Productivity can be re-written as: $\omega_{it} = \hat{\phi}_{it} - f(k_{it}, l_{it})$. For a production function approximated with a polynomial of order $\nu < \kappa$ and governed by a set of parameters α, we can now express the productivity innovation as $\xi_{it}(\alpha)$, by regressing $\omega_{it}(\alpha)$ on $\omega_{it-1}(\alpha)$ and z_{it-1}.

The coefficients of the production function are estimated with an iterative GMM procedure. The moment conditions used are $E\left[\mathscr{Z}_\nu{}' \xi_{it}(\alpha)\right] = 0$, where $\mathscr{Z}_\nu = \left(k_{it}, l_{it}, \ldots, k_{it}^{\nu_k} l_{it}^{\nu_l}\right)$ is based on the same timing assumptions for capital and labour made in Appendix A. As before, within this two-step procedure, we can directly identify both the production function coefficients α and the Markov process parameters (ρ_ω and ρ_z).

[43] To exclude the possibility of other unobservable factors that would violate the scalar unobservability assumption, one should use as many relevant observable variables as possible (with the parameter space restriction in mind).

[44] For our estimates, $\phi(\cdot)$ is approximated with a third order polynomial.

C Value-added Bias

TFP estimates under a value-added production function contain measurement error u_{it} such that: $\omega_{it} = \omega_{it}^{*} + u_{it}$, where ω_{it}^{*} is the true productivity.[45] Therefore, the Markov process for TFP can be expressed as $\omega_{it} = \rho_{\omega}\omega_{it-1} + \rho_z z_{it-1} + [\xi_{it} + u_{it} - \rho_{\omega}u_{it-1}]$. Ignoring for now the additional controls $z_{it-1} = \{proxies_{jct-1}, X_{it-1}, \phi_t, \phi_j, \phi_c\}$, the expected bias from an OLS regression is:

$$\hat{\rho}_{\omega} = \rho_{\omega} - \rho_{\omega}\left(\frac{Cov(\omega_{it-1}, u_{it-1})}{Var(\omega_{it-1})}\right) \tag{C.1}$$

This suggests a downward bias when $\rho_{\omega} > 0$, which is confirmed when comparing the estimated persistence parameters between columns 4 and 3 in Table 2.[46] To the extent that ρ_{ω} is biased, so will the coefficients ρ_z of the additional controls z_{it-1}. Without loss of generality, imposing the biased estimates in the persistence parameter means that we are actually estimating:

$$\omega_{it} - \hat{\rho}_{\omega}\omega_{it-1} = \rho_z z_{it-1} + [(\rho_{\omega} - \hat{\rho}_{\omega})\omega_{it-1} + \xi_{it} + u_{it} - \rho_{\omega}u_{it-1}] \tag{C.2}$$

where the resulting error term now includes $(\rho_{\omega} - \hat{\rho}_{\omega})\omega_{it-1}$. The expected bias for the additional controls is:

$$\hat{\rho}_z = \rho_z + (\rho_{\omega} - \hat{\rho}_{\omega})\frac{Cov(z_{it-1}, \omega_{it-1})}{Var(z_{it-1})} + \frac{Cov(z_{it-1}, u_{it})}{Var(z_{it-1})} - \rho_z\left(\frac{Cov(z_{it-1}, u_{it-1})}{Var(z_{it-1})}\right) \tag{C.3}$$

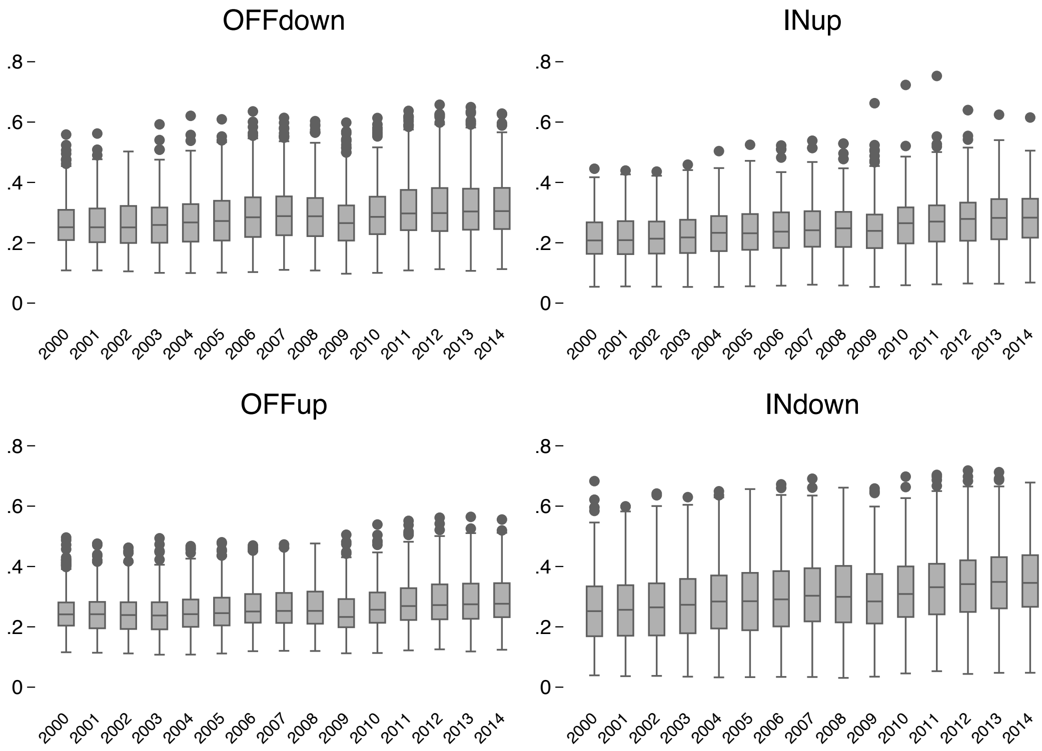
which for $\rho_{\omega} - \hat{\rho}_{\omega} > 0$ depends on the correlation of the additional controls with the lagged productivity and with the measurement error along with the sign of the estimated coefficient.

[45] In our case, measurement error does not necessarily refer to classical measurement error, i.e. mean zero and uncorrelated with the true dependent and independent variables and with the equation error. To the contrary it has a structural form since it is the outcome of a mispecified production function and thus potentially correlated with the regressand, regressors and error term. For example, in the simplest case of a Cobb-Douglass production function it can be expressed as: $u_{it} = (\alpha_m - 1)m_{it}$, where α_m is the output elasticity of materials.

[46] The exact bias is also determined by the correlation between the persistence term and measurement error: $Cov(\omega_{it-1}, u_{it})$. However, this correlation does not appear to affect the direction of the bias in our estimates.

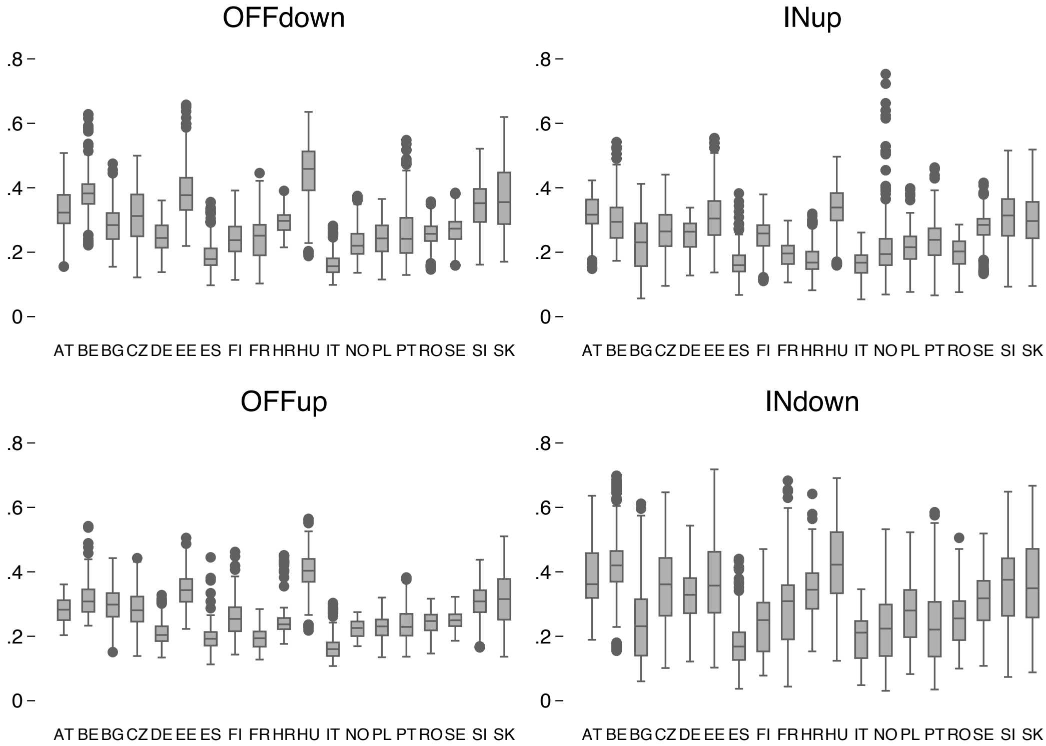
D Additional Figures and Tables

Figure D.1: Inter-industry offshoring and inshoring by year over countries and industries



Source: Authors' calculations based on WIOT.
Notes: Let x represent the variable of interest. The upper, middle and lower hinge of the box represents the 25th ($x_{[25]}$), 50th ($x_{[50]}$) and 75th ($x_{[75]}$) percentile, respectively. Define $x_{(i)}$ as the ith ordered value of x. The upper adjacent line has a value $x_{(i)}$ such that $x_{(i)} \leq U$ and $x_{(i+1)} > U$, where $U = x_{[75]} + 1.5(x_{[75]} - x_{[25]})$. The lower adjacent line has a value $x_{(i)}$ such that $x_{(i)} \geq L$ and $x_{(i+1)} < L$, where $L = x_{[25]} - 1.5(x_{[75]} - x_{[25]})$. Solid circles represent outside values.

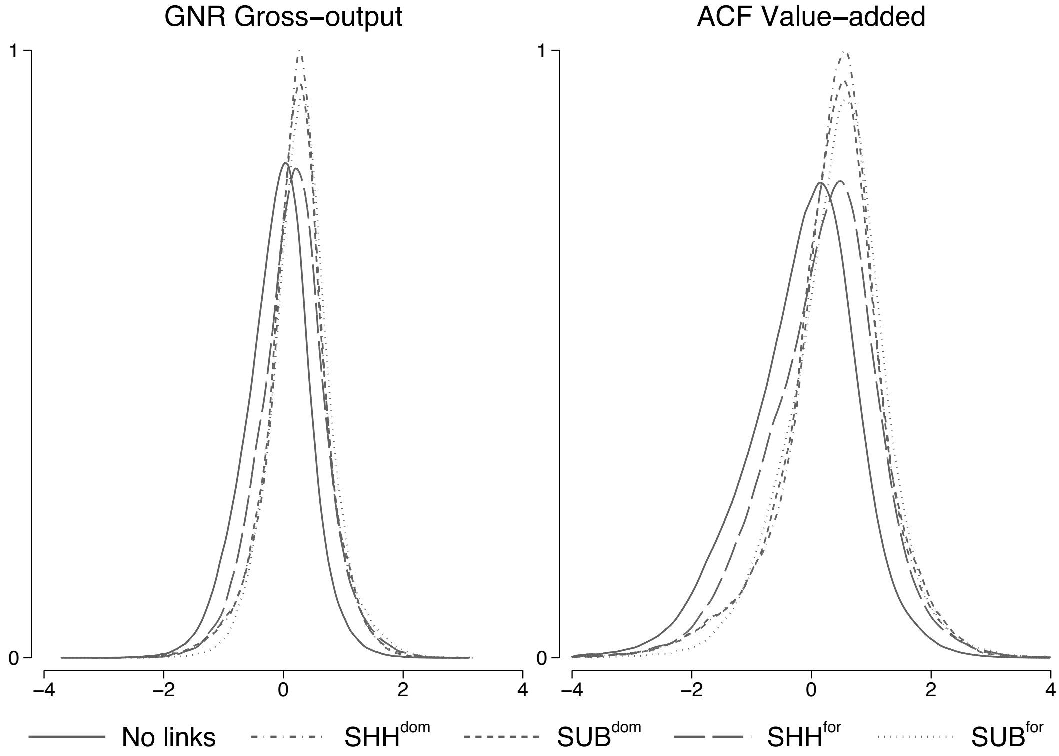
Figure D.2: Inter-industry offshoring and inshoring by country



Source: Authors' calculations based on WIOT.

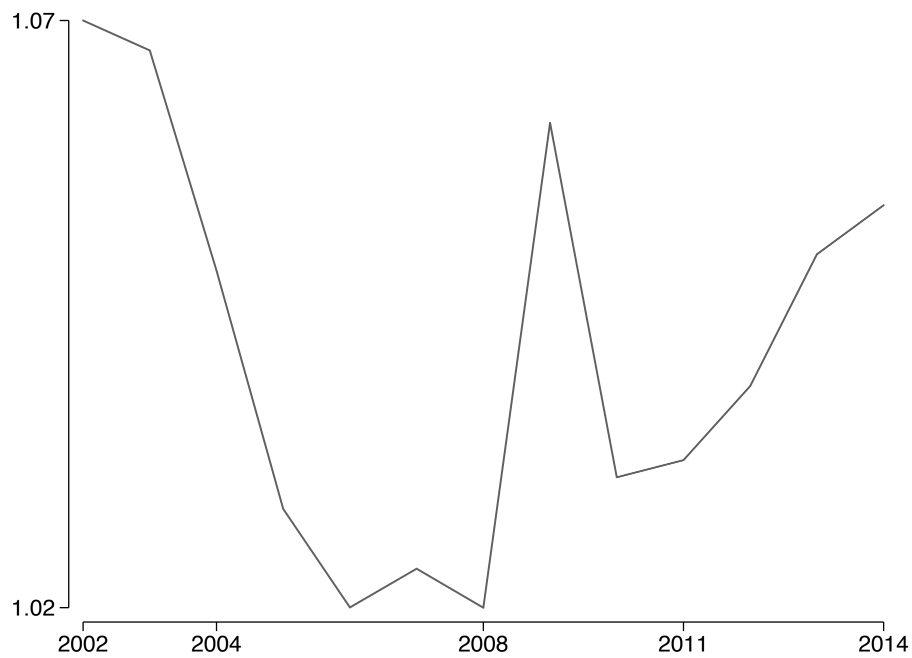
Notes: Let x represent the variable of interest. The upper, middle and lower hinge of the box represents the 25th ($x_{[25]}$), 50th ($x_{[50]}$) and 75th ($x_{[75]}$) percentile, respectively. Define $x_{(i)}$ as the ith ordered value of x. The upper adjacent line has a value $x_{(i)}$ such that $x_{(i)} \leq U$ and $x_{(i+1)} > U$, where $U = x_{[75]} + 1.5(x_{[75]} - x_{[25]})$. The lower adjacent line has a value $x_{(i)}$ such that $x_{(i)} \geq L$ and $x_{(i+1)} < L$, where $L = x_{[25]} - 1.5(x_{[75]} - x_{[25]})$. Solid circles represent outside values.

Figure D.3: Re-centered (at the industry level) distributions of estimated TFP ($\hat{\omega}_{it}$) by ownership-linked firm types



Source: Authors' calculations based on BvDEP.
Notes: For expositional ease, we focus on the $\hat{\omega}_{it}$ distributions with values between -4 and 4.

Figure D.4: Markup by year



Source: Authors' calculations based on BvDEP.

Table D.1: List of CPA and NACE 2-digit (Rev.2) industries for the manufacturing sector

CPA	NACE	Description of CPA industries
5	10t12	Manufacture of food products, beverages and tobacco products
6	13t15	Manufacture of textiles, wearing apparel and leather products
7	16	Manufacture of wood and products of wood and cork, except furniture; etc.
8	17	Manufacture of paper and paper products
9	18	Printing and reproduction of recorder media
10	19	Manufacture of coke and refined petroleum products
11	20	Manufacture of chemicals and chemical products
12	21	Manufacture of basic pharmaceutical products and preparations
13	22	Manufacture of rubber and plastic products
14	23	Manufacture of other non-metallic mineral products
15	24	Manufacture of basic metals
16	25	Manufacture of fabricated metal products, except machinery and equipment
17	26	Manufacture of computer, electronic and optical products
18	27	Manufacture of electrical equipment
19	28	Manufacture of machinery and equipment n.e.c.
20	29	Manufacture of motor vehicles, trailers and semi-trailers
21	30	Manufacture of other transport equipment
22	31t32	Manufacture of furniture; other manufacturing
23	33	Repair and installation of machinery and equipment

Note: CPA corresponds to industries in WIOD according to ISIC Rev. 4 or equivalently NACE Rev. 2 (Timmer et al. 2016).

Table D.2: Correlation of proxies

	$OFFdown$	$INup$	$OFFup$	$INdown$	OFF	IN
$OFFdown$	1.000					
$INup$	0.726	1.000				
$OFFup$	0.859	0.729	1.000			
$INdown$	0.846	0.677	0.603	1.000		
OFF	0.775	0.590	0.746	0.628	1.000	
IN	0.608	0.525	0.406	0.698	0.645	1.000

Table D.3: Robustness of TFP effects from inter-industry offshoring and inshoring under baseline specification with alternative combinations of proxies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$OFFdown_{jct-1}$	0.187***	0.149**	0.191***				0.158***			
	(0.055)	(0.058)	(0.047)				(0.033)			
$INup_{jct-1}$	0.147***	0.112**		0.136**				0.177***		
	(0.044)	(0.044)		(0.054)				(0.067)		
$OFFup_{jct-1}$	-0.035	-0.073			0.098*				0.104***	
	(0.044)	(0.057)			(0.056)				(0.038)	
$INdown_{jct-1}$	0.009	0.041				0.102***				0.125***
	(0.054)	(0.048)				(0.036)				(0.036)
OFF_{jct-1}	-0.020		-0.065*	0.017	-0.035	0.018				
	(0.062)		(0.038)	(0.035)	(0.034)	(0.041)				
IN_{jct-1}	0.052		0.080	0.056	0.096	0.025				
	(0.055)		(0.067)	(0.076)	(0.065)	(0.070)				
Observations	845,383	845,383	845,383	845,383	845,383	845,383	845,383	845,383	845,383	845,383

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include dummies for domestic and foreign ownership links ($SHH^{dom}, SUB^{dom}, SHH^{for}, SUB^{for}$), and year, industry and country fixed effects. Standard errors are computed using the nonparametric bootstrap with 199 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates. Bootstrap samples are taken independently within each strata, i.e. industry.

Table D.4: TFP effects from inter-industry offshoring and inshoring under baseline specification and robustness to alternative assumptions

	(1) Baseline	(2) Size Dummy	(3) Instruments First Diff.	(4) BACON Trim p15	(5) Bootstrap 999 Reps	(6) Bootstrap No Strata
ω_{it-1}	0.548***	0.554***	0.536***	0.487***	0.548***	0.548***
	(0.014)	(0.012)	(0.011)	(0.013)	(0.013)	(0.013)
$OFFdown_{jct-1}$	0.187***	0.078	0.193***	0.159**	0.187***	0.187***
	(0.055)	(0.055)	(0.062)	(0.067)	(0.059)	(0.055)
$INup_{jct-1}$	0.147***	0.177***	0.142***	0.161***	0.147***	0.147***
	(0.044)	(0.037)	(0.041)	(0.053)	(0.040)	(0.038)
$OFFup_{jct-1}$	-0.035	0.057	-0.076	0.158**	-0.035	-0.035
	(0.044)	(0.052)	(0.046)	(0.068)	(0.047)	(0.048)
$INdown_{jct-1}$	0.009	0.034	0.024	0.042	0.009	0.009
	(0.054)	(0.052)	(0.045)	(0.073)	(0.050)	(0.049)
$D*OFFdown_{jct-1}$		0.249***				
		(0.037)				
$D*INup_{jct-1}$		-0.054				
		(0.052)				
$D*OFFup_{jct-1}$		-0.272***				
		(0.049)				
$D*INdown_{jct-1}$		-0.065*				
		(0.035)				
Observations	845,383	845,383	845,383	885,272	845,383	845,383

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include intra-industry offshoring and inshoring, dummies for domestic and foreign ownership links ($SHH^{dom}, SUB^{dom}, SHH^{for}, SUB^{for}$), and year, industry and country fixed effects. D is a dummy variable equal to one when firms are classified as small-sized and zero when medium-large-sized. Standard errors are computed using the nonparametric bootstrap with 199 replications (except for column 5 with 999 replications) over the GNR two-step estimation procedure and are reported in parentheses below point estimates. Bootstrap samples are taken independently within each strata, i.e. industry, except for column 6 where there is no strata.

Table D.5: Heterogeneity in TFP effects from inter-industry offshoring and inshoring with sample splits

	(1) Baseline	(2) No Foreign Links	(3) Foreign Links	(4) Relatively Downstream	(5) Relatively Upstream	(6) Relatively Low-tech	(7) Relatively High-tech	(8) Labour Intensive	(9) Capital Intensive	(10) Downstream & Low-tech	(11) Downstream & High-tech	(12) Downstream & Labour-int	(13) Downstream & Capital-int
$OFFdown_{jct-1}$	0.187***	0.173***	0.149**	0.228***	0.284***	0.269***	0.280***	0.242***	0.233**	0.438***	0.223***	0.370***	-0.007
	(0.055)	(0.052)	(0.067)	(0.055)	(0.085)	(0.096)	(0.048)	(0.056)	(0.099)	(0.113)	(0.065)	(0.092)	(0.158)
$INup_{jct-1}$	0.147***	0.166***	0.132***	0.401***	-0.005	0.142	0.049	0.206**	0.084	0.330***	0.133**	0.452***	0.243*
	(0.044)	(0.028)	(0.051)	(0.078)	(0.096)	(0.095)	(0.076)	(0.093)	(0.084)	(0.086)	(0.067)	(0.093)	(0.146)
$OFFup_{jct-1}$	-0.035	-0.074*	-0.080	-0.162***	-0.014	-0.214**	-0.018	-0.048	-0.099	-0.569***	0.080	-0.255***	0.038
	(0.044)	(0.042)	(0.070)	(0.054)	(0.077)	(0.093)	(0.061)	(0.066)	(0.088)	(0.147)	(0.088)	(0.081)	(0.145)
$INdown_{jct-1}$	0.009	0.008	-0.006	-0.022	0.016	0.002	-0.002	0.029	-0.066	-0.092	0.014	-0.131**	0.100
	(0.054)	(0.045)	(0.050)	(0.065)	(0.098)	(0.100)	(0.049)	(0.067)	(0.083)	(0.089)	(0.072)	(0.064)	(0.173)
Observations	845,383	750,176	95,207	442,718	402,663	334,381	511,000	509,430	335,951	252,763	189,955	298,070	144,648

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include intra-industry offshoring and inshoring, dummies for domestic and foreign ownership links ($SHH^{dom}, SUB^{dom}, SHH^{for}, SUB^{for}$), and year, industry and country fixed effects. Standard errors are computed using the nonparametric bootstrap with 199 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates. Bootstrap samples are taken independently within each strata, i.e. industry.

Table D.6: Upstreamness measure

Production Line Position	CPA	(1) *Mean EU*	(2) *Mean*
1	12	1.42	1.29
2	22	1.47	1.35
3	21	1.48	1.38
4	17	1.52	1.24
5	20	1.55	1.21
6	6	1.56	1.29
7	5	1.59	1.48
8	19	1.60	1.31
9	18	1.87	1.34
10	10	1.98	2.42
11	23	2.03	2.02
12	11	2.17	1.50
13	13	2.31	1.70
14	16	2.32	1.86
15	7	2.38	1.87
16	14	2.38	1.98
17	8	2.45	1.70
18	15	2.64	1.60
19	9	2.84	2.55

Notes: Computed as in Fally (2012) and Antràs et al. (2012) using the WIOT. The upstreamness measure in column 1 considers EU as one entity and is computed for each industry and year using the sum of WIOT across all 19 EU countries. The upstreamness measure in column 2 is computed for each industry, year and country using the respective WIOT. *Mean EU* represents the mean value of the computed EU wide upstreamness measure from 2000 to 2014 for each industry. *Mean* represents the mean value of the computed country-specific upstreamness measure across all EU countries from 2000 to 2014 for each industry. Larger values represent more upstream industries.