Productivity effects from inter-industry offshoring and inshoring: Firm-level evidence from Belgium.

Bruno Merlevede* Angelos Theodorakopoulos†

*Ghent University, HUBrussel and IWH

†Ghent University

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Abstract

In this paper we confirm the existence of enhancements on firm productivity as domestic upstream and downstream clients become more internationalised and therefore offshore (import intermediate inputs) and inshore (export final output for intermediate input usage) intensively. China's accession to the WTO, which in the case of Belgium is experienced as reducing trade barriers to a trading destination (China), help us confirm that these inter-industry productivity improvements can also be generated from a quasi-trade liberalisation event. These improvements represent approximately one third of the average increase in productivity of Belgian manufacturing firms during 2002-2007. Upstream linkages are the dominant source of these productivity benefits and are ripped mainly from medium-low tech, relatively labor intensive and relatively upstream industries. Finally, we draw upon the importance on our results of value added bias in production function estimations and misspecification bias when ignoring the dynamic nature of productivity.

Keywords: Offshoring, supply chain, spillovers, productivity
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*Department of economics Ghent university, Tweekerkenstraat 2, B-9000 Ghent, Belgium, e-mail: bruno.merlevede@ugent.be

†Corresponding author: Department of Economics, Ghent University, Tweekerkenstraat 2, B-9000 Ghent, Belgium, e-mail: angelos.theodorakopoulos@ugent.be, tel. +32(0)9 264 34 79

1 Introduction

The fragmentation of production across national boundaries has been a distinct feature of the world economy in recent decades (Antràs et al., 2012). Part of this fragmentation is attributed to increased opportunities for offshoring, i.e sourcing intermediate inputs in the production process from foreign suppliers.[1] This is prevalent in the global economy where approximately two thirds of international trade volume is accounted by shipments of intermediate inputs (Johnson and Noguera, 2012).

The slice up of the production function in conjunction with the decrease in trade and communication costs over the years, resulted in increasingly geographically fragmented value chains. In turn, this greatly impacted firm performance. Strand of the literature has examined the effects on productivity induced by changes in the offshoring intensity of firms within the industry, i.e *intra-industry* offshoring.[2] It has neglected though potential home country effects on productivity from *inter-industry* offshoring. With inter-industry offshoring we refer to the offshoring activity undertaken by domestic downstream clients or upstream suppliers of the focal firm.

Parallel to that, we notice that the literature is silent about inshoring. The term refers to the mirror action of offshoring and is defined as the export of final goods that will be used for intermediate input usage to both affiliated and unaffiliated firms in a foreign country.[3] Similarly, potential home country effects on productivity from inter-industry inshoring are neglected. Inter-industry inshoring refers to the inshoring activity undertaken by domestic downstream clients or upstream suppliers of the focal firm.

With this paper we try to answer the following three questions. First, we seek to identify whether inter-industry linkages can serve as channels via which intermediate input-induced trade generates technology capabilities as measured by productivity gains. Second, we ask whether "opening up" to trade, which in the case of Belgian firms can be considered as an exogenous trade barrier reduction to China, will impact firms' productivity via the prementioned inter-industry channels. Finally, we draw upon the importance of mitigating value-added bias on production function estimations and misspecified models that would render our results inconsistent.

Using firm level data for Belgian manufacturing firms during 2002-2007, we retrieve firm-level productivity estimates. We follow a flexible two-step procedure for gross output production functions as in Gandhi et al. (2012) (henceforth GNR), that corrects for value-added bias. From Input-Output tables we construct industry-level measures to proxy the inter-industry offshoring and inshoring intensities based on a measure proposed by Merlevede and Michel (2013). We estimate the effects of inter-industry offshoring and inshoring intensities on productivity with both one-stage and two-stage procedures in close relation to De Loecker (2013); Fernandes (2007); Topalova and Khandelwal (2011). Special attention is paid on how we specify our equations and the exogeneity of the variables of interest. We raise concerns over misspecification and value added bias in the estimating equation and the importance for careful consideration on the dynamic nature of the law of motion of productivity.

From the first set of results we find strong evidence over the existence of inter-industry offshoring and inshoring effects on productivity of the focal firms. Overall, inter-industry trade of intermediate inputs resulted on an average productivity increase of 3.31% for Belgian manufacturing firms over the period 2002-2007. This suggests that productivity improvements from inter-industry linkages represent approximately 2 times the average TFP increase of Belgian

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

[2]See Amiti and Wei (2005); Görg et al. (2008); Halpern et al. (2009); Ito and Tanaka (2010); Michel and Rycx (2014); Tomiura (2007).

[3]The term was initially inspired by Slaughter (2004) that used "insourcing" as the converse dimension of outsourcing including only foreign direct investments, but was coined by Liu and Trefler (2008) that used it for the case of unaffiliated companies and its effect on labor market.

manufacturing firms during 2002-2007. The bulk of positive effects mainly originates from upstream supply chain linkages, while medium-low tech (relatively less RnD intensive), relatively labor intensive or relatively upstream industries are the main recipients of these effects.

For the second set of results, we first need to argue that China's accession to the WTO in 2001 can be considered as an exogenous quasi-trade liberalisation event for Belgian firms. Since the end of 2001 Belgium-China's bilateral trade restrictions fell sharply. Therefore, China is considered as a "new" trading partner for Belgium. In turn, this implies an exogenous variation in trade statistics and in our case in the proxies of interest (see figure 2). This allows us to argue that productivity enhancements from inter-industry offshoring and inshoring were induced by this quasi-trade liberalisation event. This amounts to a 0.5% increase in the average productivity of Belgian firms and corresponds to 30% of the total increase in average productivity of Belgian manufacturing firms during the period 2002-2007. Again, medium-low tech (relatively less RnD intensive) and relatively labor intensive industries rip all the benefits with the only channel being upstream offshoring to China.

For the last set of results, we compare our previous estimates with results based on a typical in the production function estimation literature two-step procedure as in Ackerberg et al. (2006)(henceforth ACF) using a value-added function. Under such structure, the value added bias leads to economic effects that are severely overstated from 3-10 percentage points.

The rest of the paper is organised as follows. Section 2 provides an overview of the existing literature over the relationship between productivity, supply chain, offshoring/inshoring and trade liberalisation. Section 3 describes the data. Section 4 focuses on the definition, construction and analysis of trends for the relevant proxies, while Section 5, describes the empirical methodology. Section 6 presents the results, section 7 presents robustness results and section 8 concludes.

2 Related Literature

The link between international trade and productivity has been under scrutiny but still bares major challenges. A big strand of the literature is devoted on the link between imported intermediate inputs and firm productivity. Theoretical models suggest various channels through which imported intermediate inputs affect productivity. Such channels include access to potentially higher quality inputs as in quality-ladder models, access to more varieties of intermediate inputs and learning from importing (Aghion and Howitt, 1992; Antras et al., 2014; Connolly, 2003; Dragusanu, 2014; Grossman and Helpman, 1991; Markusen, 1989). Empirical research, at the firm and sectoral-level, has on average confirmed strong increases in the productivity of firms from importing intermediate inputs (Bernard et al., 2007, 2009; Feenstra et al., 1992; Halpern et al., 2009; Kasahara and Lapham, 2013, 2008; Muendler, 2004). In close relation to this literature, studies under the alternative definition for imported intermediate inputs, named as offshoring or international outsourcing, have reported similar outcomes (Amiti and Wei, 2009; Egger and Egger, 2006; Görg et al., 2008; Kurz, 2006; Tomiura, 2007).

This strand of international economics was preceded by research over the relationship between export behavior and firm productivity. Influential seminal theoretical papers of Melitz (2003) and Bernard et al. (2003) derive the productivity premium of exporting firms, while extensive empirical research strongly confirms such predictions.[4] Exporting is considered as the action of selling final output to consumers abroad. Up to our knowledge, no attention has been paid to the effect on firm's productivity from exporting final output for intermediate input use to firms abroad i.e inshoring.

All prementioned studies, focus on the direct or within firm/industry effects from importing intermediate inputs or exporting. But firms operate in a complex environment where they are supplied from domestic upstream industries and possibly supply domestic downstream industries.

[4]Both theoretical and empirical literature can be reviewed from the following non-exhaustive sources: Bernard et al. (2011); Melitz and Redding (2012); Redding (2010).

If these domestic upstream and downstream industries become more productive from importing or exporting intermediate inputs as described above, we would expect this exposure to foreign technology to be transmitted downstream and upstream respectively. This notion and the mechanisms behind it are closely related to vertical technology transfers from FDI as in Blalock and Gertler (2008); Javorcik (2004). In our case, the conduit will not be FDI but offshoring and inshoring activity.

The only relevant research is by Blalock and Veloso (2007), showing that Indonesian firms in industries supplying increasingly import-intensive industries have on average higher productivity growth. This suggests that linkages of vertical supply relationships offer an additional channel through which import-driven technology transfers can occur. It should be noted though that their focus is on vertical supply relationships of import driven technology transfers, while ignoring vertical demand relationships. Also, they ignore vertical supply and demand relationships of export driven technology transfers that could serve as new channels. Neglecting all those linkages and their possible interactions could affect both the scale and direction of results due to omitted variable bias (Amiti and Konings, 2007).[5]

This paper fills in those gaps in trade literature by identifying in a holistic approach the effects on productivity from offshoring and inshoring via inter-industry linkages. Also, we bring up the importance of trade openness on firm performance via inter-industry linkages. Finally, we emphasize over the significance of value-added bias in production function estimations and misspecification bias resulting from not correctly accounting for the dynamic nature of productivity.

3 Data

Firm-level data for a panel of Belgian manufacturing firms from 2002 to 2007 are taken from Amadeus database maintained by Bureau van Dijk Electronic Publishing (2011) (BvDEP). BvDEP updates its information every month with DVD's that contain only the latest information on ownership. Also, firms that exit the market are dropped out of the searchable database fairly easily. Therefore, for full overview of financial and ownership information over time multiple DVD's are used to construct the database. This allows us to build a parent-affiliate dataset with nearly full financial and administrative information i.e. balance sheet, profit and loss account, activities, location, ownership. For further details over the construction and representativeness of the data refer to Merlevede et al. (2015).

For the panel of Belgian firms during 2002-2007, we focus on the sample of active manufacturing firms filling unconsolidated accounts. For an overview of the NACE rev.1.1 2-digit industries included see Table 1. We keep firms reporting operating revenue, tangible fixed assets, number of employees, costs of employees, material inputs, NACE 2-digit level industry classification, NUTS region classification, date of incorporation, and ownership information. For each industry we drop outliers detected using the multiple outlier detection method named as block adaptive computationally efficient outlier nominators (BACON) proposed by Billor et al. (2000).[6] Firms that re-enter or stay for maximum two years are dropped. Also, the Manufacture of Leather, Leather and Footwear and the Manufacture of Coke, Refined Petroleum and Nuclear Fuel Products are dropped for insufficient number of observations for estimating a production function at the industry level. In sum, we end up with an unbalanced panel of 2765 firms and 15496 observations for the period 2002-2007 (see Table 2).

All monetary variables are deflated using the appropriate NACE 2-digit deflator. Our main data source for output deflators is the EU KLEMS database. Deflators have been incorporated

[5]In addition, their procedure is based on production function estimation where they introduce their proxy as an input, casting doubts about the validity of their approach (De Loecker and Goldberg, 2013).

[6]The variables used include log values of operating revenue, labor, capital and material input. From the total sample 1.8% is dropped.

and updated by Eurostat. Real output *(Y)* is the operating revenue deflated with producer price indices. Capital *(K)* is tangible fixed assets deflated by the average of the deflators for five NACE 2-digit industries: machinery and equipment (29); office machinery and computing (30); electrical machinery and apparatus (31); motor vehicles, trailers, and semi-trailers (34); and other transport equipment (35) (Javorcik, 2004). Real material inputs *(M)* is material inputs deflated by an intermediate input deflator as a weighted average of output deflators where country-time-industry specific weights are based on intermediate input uses retrieved from input-output tables. Labor *(L)* is obtained as the number of employees. Firm wage *(W)* is measured as the share of cost of employees over the number of employees.[7]

For the measurement of proxies we use the freely available online World Input-Output Database (WIOD). It is a time-series of Input-Output (IO) tables for forty countries worldwide and a model for the rest of the world, covering the period from 1995 to 2011.[8] It also contains information for international supply and use tables (Int. SUTs) in current prices, expressed in millions of dollars that will allow us to compute our proxies based on the origin of the foreign country offshoring to and inshoring from. Note that the WIOD industry classification (CPA) is more aggregate compared to the Eurostat IO tables, containing 35 industries and 59 products.[9]

The major advantage over other databases is that it varies over time and by origin of the destination country. In addition, imports of goods do not rely on the standard and popular in the literature proportionality assumption. A more flexible approach is followed where import proportions vary across end-use categories and most importantly, within each end-use category they also differ by country of origin.[10] This will provide greater variability over time and across different types of intermediate inputs and countries of origin. We expect this extra level of detail to unmask possible heterogeneity and provide better identification.

4 Inter-industry Offshoring and Inshoring

4.1 Definition and Measurement

For the measurement of the inter-industry offshoring and inshoring activity, relevant proxies will be constructed at the industry-year level using WIOD. For downstream offshoring, we follow the measure proposed by Merlevede and Michel (2013) and parallel to that, we introduce for the first time a proxy for upstream offshoring:

$$Down\_off_{jt} = \sum_{d \neq j} \theta_{jdt} \Phi_{jdt} \qquad \text{and} \qquad Up\_off_{jt} = \sum_{u \neq j} \zeta_{jut} \Psi_{jut} \tag{1}$$

where θ_{jdt} is the proportion of industry j's output supplied to downstream industry d at time t and similarly ζ_{jdt} is the proportion of industry j's intermediate inputs supplied from upstream industries u at time t. We fix the weights to year 2000 values in order to eliminate distortion of relative magnitudes across time and industries and bring exact identification of *inter-industry* effects. It helps to mitigate endogeneity, since any decision of the firm to supply or be supplied with intermediate inputs is fixed to two years prior to the start of our sample. This will render the proxy orthogonal to the idiosyncratic error of productivity.

The extent to which the offshoring intensity of each downstream industry d or upstream industry u affects industry j is represented by Φ_{jdt} and Ψ_{jut} respectively. These weights are

[7] We make sure that the minimum wage concept holds. In Belgium this translates to approximately 15000 Euro/year (OECD , 2015).

[8] Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China (includes Macao and Hong Kong), Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Korea, Malta, Mexico, Netherlands, Portugal, Poland, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Taiwan, Turkey, UK, USA.

[9] For a correspondence with the NACE 2-digit see Table 1.

[10] For detailed information over the construction of the WIOD tables see Dietzenbacher et al. (2013).

computed using a weighted sum of the offshoring intensity for only the products that industry j supplies downstream industry d or is supplied from upstream industry u respectively and are offshored by the later two. This refinement departs from simple industry averages common in the literature, allowing for more precise identification of the effects by capturing the importance of secondary outputs. For example, the downstream offshoring proxy can be seen as a downstream demand side shock from importing intermediate inputs or equivalently as downstream import competition. The focal firms have to compete with foreign firms for the supply of intermediate inputs in downstream industries. On the other hand, upstream offshoring is the supply side shock of importing intermediate inputs. In this case the mechanism is different as here we expect the diffusion of knowledge spillovers from upstream to downstream industries (see Coe and Helpman (1995); Connolly (2003); Grossman and Helpman (1994)).

Overall, they are inherently relative measures that are interpreted as: firms with larger values for $Down\_off_{jt}$ (Up_off_{jt}) are those that face relatively more downstream (upstream) offshoring.

Inter-industry inshoring, represents the mirror action of *inter-industry* offshoring. It can be seen as a niche category of exporting where firms in downstream and upstream industries export their final output as intermediate inputs to foreign firms while at the same time they are supplied or supply the focal firms with intermediate inputs. The relevant proxies defined as downstream inshoring ($Down\_in_{jt}$) and upstream inshoring (Up_in_{jt}) will be computed and interpreted in line with the earlier approach.

Exploiting the richness of the WIOD, we can split the proxies according to the origin of the trading partner, i.e China. For an in depth analysis over the construction of the proxies and inherent possible mechanisms see Appendix A.

4.2 Trends for Proxies

Given the variety of proxies in our analysis, we go through a visual inspection of their evolution over time. In Figure 1, we observe the average inter-industry offshoring and inshoring intensities for all manufacturing firms in each year. The left figure shows downstream offshroring fluctuating vastly over the years leading to an average increase during 2002-2007. This idea is in line with the concept of firms in developed countries operating under a stable environment where they are aware of the domestic market, the offshoring "opportunities" and also their needs for intermediate inputs. Therefore, firms adjust fast to a wider set of offshoring opportunities. On the other hand upstream offshoring revealed a stable decrease over time that is consistent with value chains becoming less vertically fragmented over time and a shift of value added towards industries that are closer to final demand (Fally, 2011).

The right figure, clearly depicts that downstream and upstream inshoring increase significantly over time. Inshoring is a niche exporting action, where we consider final products that are exported for intermediate use only. This trend is in line with Belgium being a small open and heavily trade oriented economy, where in 2007 the exports of goods and services represented 77.5% of the country's GDP and has been growing since 1995 (OECD, 2015).

Figure 2, depicts the evolution of our proxies as before, but now they are specific to China as a trading partner. By making the proxies destination specific, we expect to unmask possible heterogeneity in the data. The choice of China is important as its accession to the WTO on December 2001, provides a large degree of exogenous variation in trading activities of Belgium with China and consequently to our proxies. As a result, Belgium faces a quasi opening up to trade with a specific country. It is clearly depicted that since 2001 all proxies show an upward shift in trend. Overall, China's accession to the WTO will allow us to argue over the causal effect of trade openness on TFP via interindustry linkages.

5 Empirical Methodology

5.1 Productivity

Productivity estimates are recovered as the estimated residuals of a production function. First, we consider a flexible, and log additive in the Hicks-neutral productivity shock, gross output production function, $Y_{it} = F_t(K_{it}, L_{it}, M_{it})e^{\omega_{it}+\epsilon_{it}}$ that applies to all firms. In logs, the production function to be estimated for each industry is of the following form:

$$y_{it} = f_t(k_{it}, l_{it}, m_{it}) + \omega_{it} + \epsilon_{it} \tag{2}$$

where y_{it}, k_{it}, m_{it} are log values of deflated at the industry level operating revenue, capital and material respectively and l_{it} is the log of total number of employees for firm i at time t. Productivity ω_{it}, is unobserved to the econometrician but known to the firm, while ϵ_{it} picks up shocks ex-post to firm's decisions.[11]

Up to now, the applied production function estimation literature, has been mainly employing structural approaches including both dynamic panel methods (Arellano and Bond, 1991; Blundell and Bond, 1998, 2000) and proxy variable methods (Ackerberg et al., 2006; Levinsohn and Petrin, 2003; Olley and Pakes, 1996; Wooldridge, 2009)(henceforth OP, LP, ACF and Wooldridge respectively). The main focus is to solve for the endogeneity issue, known as "simultaneity or transmission bias", originating from the fact that firms choose inputs while knowing their productivity level (Griliches and Mairesse, 1999; Marschak and Andrews, 1944).

Despite their popularity and prevalence, proxy variable methods suffer from identification issues when the production function contains flexible inputs such as material. These issues have been pointed out by Ackerberg et al. (2006); Bond and Söderbom (2005); Marschak and Andrews (1944); Mendershausen (1938) and formalised by GNR. Intuitively, there is not enough variation outside the production function system to identify the flexible variable input.[12]

To circumvent this problem, applied economists focus on a value added production function. This specification has been well developed in the literature but conceptually fails to identify the "true" variables of interest such as productivity and imposes strong assumptions (Bruno, 1978; Diewert, 1978). As a result, estimates suffer from a "value added bias" overstating the dispersion in productivity and the heterogeneity across industries. The later is an at least equally important source of bias as the "transmission bias". Productivity margins of the variables of interest, such as exporting/importing activity, are significantly overestimated resulting to a distorted image of the true impact and consequently misleading policy implications (Rivers (2013);GNR).

Under these considerations, GNR propose a simple nonparametric estimator for the production function and productivity. They establish identification by exploiting information in the first order condition with respect to the variable input from firm's static profit maximization problem. This flexible approach controls for both transmission and value added bias. It imposes no specific functional form for the production function.In addition it does not rely on strong assumptions, necessary for the proxy variable framework, in order to invert the proxy demand function, such as scalar unobservability or bijection (see OP, LP, ACF, ABBP,GNR). The procedure follows two steps in line with most of the the proxy variable methods but exploits information within the model to secure identification.

Overall estimation of the production function is at the CPA industry level, based on the two step non-parametric estimator of GNR. Using estimates of the production function coefficients

[11]Given that y_{it} is an observable variable in our dataset we expect ϵ_{it} to also contain measurement error to output and prices, assumed to be symmetric across firms within each industry.

[12]Firm specific prices, up to the extent they are exogenous, can potentially serve as instruments for flexible inputs and solve for the identification problem (Doraszelski and Jaumandreu, 2013). However, in practice it is hard to find prices at the firm/plant level that reflect differences in expected and not chosen prices (Ackerberg et al., 2007; Griliches and Mairesse, 1999) (henceforth GM and ABBP, respectively). Therefore, in most datasets prices will capture market power and input/output quality differences rendering them endogenous (Atalay, 2014; Fox and Smeets, 2011; Kugler and Verhoogen, 2012).

at the CPA industry level, we retrieve productivity estimates $\hat{\omega_{it}}$ for firm i in industry j at time t (TFP). For a detailed description over the assumptions and steps followed refer to Appendix B and GNR.

It is important to emphasize that the term TFP is not identical to disembodied technological change, often referred to as "Solow Residual" (Solow, 1957). In practice it also includes the impact of inputs that are not explicitly measured as such, like intangibles that include marketing, management and human capital skills among others. In addition, we should explicitly state that our TFP estimates are revenue based since we do not observe physical output, but only deflated at the industry level monetary values. Therefore, TFP estimates will contain price variation away from the industry deflator and any results should be interpreted with this caveat in mind.[13]

5.2 Effects of Inter-industry Offshoring and Inshoring on TFP

5.2.1 Two-stage

To investigate the inter-industry effects of offshoring and inshoring on firm-level productivity, we allow the proxies to shift the technology parameter of the production function, ω_{it}. This is a typical approach in the literature of international trade and is based on a two-stage process. The first stage, is the estimation of TFP from the two-step process described above. The second stage, is the specification of the equation that will relate the variables of interest with TFP. A non-negligible part of the literature employs a static specification:

$$\hat{\omega}_{ijt} = \gamma_c + \gamma_p f(proxies_{jt-1}) + \gamma_x X_{it-1} + \alpha_t + \alpha_j + \alpha_r + \xi_{ijt} \tag{3}$$

where $f(proxies_{jt-1})$ is the vector of proxies, X_{it-1} a vector of MNC, SHH_BE and SUB_BE status and α_t, α_j and α_r a set of dummies for time, industry and region fixed effects respectively.[14] In this case though, as first noticed by Fernandes (2007), there is a conceptual gap between the two stages. Stage one, assumes a Markov process for productivity, while stage two uses a static specification for productivity ignoring the dynamic nature of TFP. Therefore, the absence of persistence results in serial correlation that is not eliminated with fixed effects. Overall, equation (3) is misspecified. To solve for this the following dynamic specification is considered:

$$\hat{\omega}_{ijt} = \gamma_c + \rho\hat{\omega}_{i(j)t-1} + \gamma_p f(proxies_{jt-1}) + \gamma_x X_{i(j)t-1} + \alpha_t + \alpha_j + \alpha_r + \xi_{ijt} \tag{4}$$

By pooling across all firms in the sample we consistently estimate the above equation since the number of industries and regions is small compared to the panel dimension.

In the case of firm fixed effects the above specification is inconsistent. To solve the endogeneity induced by the dynamic nature of the depended variable we also apply a "System GMM" approach (SGMM).[15] This process merges two closely related dynamic panel-data models. The first, is the Arellano and Bond (1991) estimator that is sometimes called "Difference GMM". The second, is an augmented version outlined by Arellano and Bover (1995) and implemented by Blundell and Bond (1998).[16] It is important to mention here that this procedure also controls for measurement error introduced from the use of estimated lagged TFP in our specification. This is because lagged values of $\hat{\omega}_{ijt-1}$ are assumed to have measurement error not correlated with $\hat{\omega}_{ijt-1}$'s measurement error.

[13]In the robustness section we provide results for the case of imperfect competition in the output market. More structure is imposed but estimation is similar.

[14]SHH_BE and SUB_BE are dummies that indicate the case where a firm is owned by at least one Belgian firm or owns at least one Belgian firm respectively.

[15]Fernandes (2007); Topalova and Khandelwal (2011) use the Arellano and Bond (1991) approach. But as noted by Blundell and Bond (1998) the later performs purely when $\hat{\omega}_{ijt}$ is close to a random walk.

[16]For an overview of the literature and *xtabond2* estimation command of Stata, refer to Roodman (2009).

5.2.2 One-stage

Another conceptual problem of the two-stage approach is that in equation (4), conditional on lagged productivity, current productivity depends on the proxies and other determinants that are in firm's information set by the time decisions are made. On the other hand, under the Markov process assumption used in our estimation procedure, we do not take into account these inter-industry effects. To solve for this incosistency, we will include in the law of motion the relevant proxies, $\omega_{it} = g_{it}(\omega_{it-1}, s_{it-1}, f(proxies_{jt-1})) + \alpha_t + \alpha_j + \alpha_r + \xi_{it}$ and estimate them within the GNR two step procedure (Aw et al., 2008; De Loecker and Goldberg, 2013). We define this as one-stage procedure.[17] Because the proxies are industry-year specific, we are forced to estimate the production function at a more aggregate level in order to exert variability. Therefore, it is imperative to use time (α_t) and industry (α_j) fixed effects that will account for macroeconomic shocks and aggregate structural differences\changes in the economy respectively.[18]

For the two-stage procedure the inclusion of estimated productivity in the second stage introduces measurement error that will deflate the standard errors. For the one-stage procedure there is no closed form solution for the standard errors. To accommodate both concerns, bootstrapping is applied. We block-bootstrap the hole procedure by sampling with replacement, within the same industry, the firm for all the years observed in the original sample.

Overall, one-stage is the correctly specified approach upon which inference will be drawn.

5.3 Endogeneity

In the case of intra-industry offshoring and inshoring, in order to be consistent with the timing assumptions for material inputs used for the estimation of *TFP*, we expect the relevant intra-industry proxies to contemporaneously affect firm productivity. This is because material and service inputs used in the production process are freely variable, i.e no or infinitesimal adjustment costs. In this case, the decision to offshore or inshore is endogenous to the firm and should be taken into account accordingly.[19]

In our case, however, we focus on the inter-industry effects where the shocks on productivity are transmitted through relevant linkages from firms in upstream or downstream industries. To control for possible endogeneity we adopt the following approaches. First off all, in all proxies we keep fixed to values of year 2000 the technical coefficients θ_{jdt} and ζ_{jdt}. This way we eliminate from our proxies the endogenous choice of the focal firm over which downstream or upstream firms to cooperate with. Any variation originating from market structural changes or own firm characteristics will be absent and proxies will provide exact identification of the effects under consideration.

Secondly, we assume that both the existence of supply chains and most importantly the fact that the activity of upstream or downstream firms is not directly observed by the focal firm, create frictions that result in a delay in the transmission of the shock. To capture this sluggishness we use one year lag of the relevant proxies in all the specifications considered. This will alleviate concerns for simultaneity bias problem as it is counter-intuitive to argue that current TFP of firms can affect their lagged values of inter-industry offshoring and inshoring.

Finally and most importantly, our proxies are constructed in such a way that it is possible to have transfers from the focal firm to upstream or downstream affiliated firms. Therefore, the focal firm is likely to have an impact over the upstream and downstream firms' choices. This

[17] Fernandes (2007); Topalova and Khandelwal (2011), use a direct approach by incorporating in the first-step's control function for productivity, the variables of interest. This approach is problematic because it ignores the dynamic nature of TFP and provides an irrelevant to our research equilibrium relationship between TFP and variables of interest. It only helps to control for unobserved price changes induced from the relevant shocks.

[18] A specification that accounts for firm fixed effects within the two-step procedure of GNR will be considered in the robustness section.

[19] See Amiti and Wei (2005); Görg et al. (2008); Ito and Tanaka (2010); Michel and Rycx (2014).

would render the proxies as endogenous. To control for this possibility, we exploit richness of the Amadeus database and construct variables where we know if the focal firm owns at least one domestic subsidiary (SUB_BE) or is owned by at least another domestic firm (SHH_BE). Using the above controls and the multinational status of the firm we control for any type of demand or supply chain relationship between domestic parent and affiliate firms. For the rest of the paper, we consider the lagged values of the proxies as exogenous and thus orthogonal to the error term.

6 Results

In this section we report the effects of inter-industry offshoring and inshoring on TFP, the effects of inter-industry offshoring to China and inshoring from China on TFP and the importance of valued-added bias for our results. The variables included in every specification include all inter-industry offshoring and inshoring proxies described above, i.e downstream offshoring, upstream offshoring, downstream inshoring and upstream inshoring. Separate regressions for each proxy would run the risk of omitted variable bias. The reason to avoid doing so is that we would exclude possible supply or demand linkages. These linkages and their interactions could have offsetting impacts for some mechanisms i.e x-inefficiencies reductions or multiplying effects for others i.e innovation and knowledge spillovers.

To test our concerns, for all estimations that follow, separate regressions for each proxy or combinations of them are estimated. In nearly all cases, estimated coefficients appear with the same sign but with differences in scale leading to a misleading overall interpretable impact for each effect. These differences are prevalent for upstream and downstream inshoring variables.[20]

Based on Fally (2011), RnD intensive industries became relatively less fragmented over time. Therefore, less RnD intensive industries are expected to on average absorb most of the productivity effects induced from inter-industry offshoring and inshoring. To unmask this heterogeneity, we pool all regressions over the following two categories: high-medium technology industries and medium-low technology industries.[21]

Further heterogeneity can be uncovered once we consider the work of Antràs (2003), where on a property-rights based model, the internationalisation decision can depend on capital intensity. Capital-intensive industries are more likely to be integrated (intra-firm trade) as they rely more on investment decisions taken by headquarters, while labor-intensive industries outsource more (both domestic and foreign outsourcing) since decisions taken by suppliers are relatively more important. Therefore, relatively less labor intensive industries are expected to on average absorb most of the productivity effects that would be mainly generated from upstream linkages.[22]

Continuing, Fally (2011) establishes a large shift of value added towards final stages of production i.e relatively downstream. Also, he suggests that developed countries have comparative advantage in goods that involve fewer production stages and goods that are closer to final demand. This is also in line with Antràs et al. (2012), where better rule of law, strong financial development and relative skill intensity abundance are correlated with a propensity to export in relatively more downstream industries. This translates to relatively downstream industries selling their output to end users for final use and exporting more intensively. Overall, less output is expected to end up for domestic exchange in relatively downstream sectors and therefore relatively upstream industries are prone to absorb most of the productivity effects from inter-industry linkages.[23]

[20]For a similar treatment see Amiti and Konings (2007). Results are not reported but available upon request.

[21]Definition of categories is based on RnD intensities of each industry as defined in Eurostat (2015). High-Medium Tech includes industries with CPA:9,13,14,15 and Medium-Low Tech industries with CPA:3,4,5,6,7,8,10,11,12,16. See Table 1 for correspondence with NACE 2-digit(rev.1).

[22]Capital and labor intensive industries are defined based on the median value of the distribution of average capital/labor ratios for each industry. Relatively capital intensive includes industries with CPA:3,6,7,9,10,11 and relatively labor intensive industries with CPA:4,12,13,14,15,16. See Table 1 for correspondence with NACE 2-digit(rev.1).

[23]Theoretical predictions of Antràs and Chor (2013) show that the incentive to integrate suppliers varies

To account for this possible heterogeneity, we generate an industry-level measure of relative production-line position as in Antràs et al. (2012); Fally (2011) using the WIOT database. This measure of industry upstreamness will give the average "distance" of each industry from final use. We rank industries as relatively upstream or downstream based on the median value of the distribution of the upstreamness measure as in Table 5.[24] We observe that primary and resource-extracting industries tend to be relatively upstream as in Antràs et al. (2012).

6.1 TFP Specifications and Structure

For each Table in this section, we report the static specification (3) (FE), the dynamic specification (4) (DFE), the SGMM approach of the specification (4) with firm fixed effects (SGMM) and the One-stage procedure (One-stage).[25] Regressions always include time, industry and region dummies but for the sake of space we do not report them in the tables. Further control variables include lagged MNC, SUB_BE and SHH_BE status and will be reported only in the first table as they remain unchanged for all cases. Note that as discussed in the previous section, their inclusion is imperative in order to control for possible endogeneity. An interesting take away from these variables is that for all specifications they are insignificant and with negligibly low magnitudes. At this point this is puzzling compared to theoretical and empirical literature but the cause of this result will be discussed in detail in section 6.4.

Eventhough misspecified, the reason we report static specification (3), is its frequent use in the empirical trade literature, as discussed above. Going through Tables 6-13 we observe that the sign, scale and significance of the coefficients are not consistent with the rest of specifications, leading to incorrect inference. Therefore, it is crucial to at least consider the dynamic nature of productivity in order to avoid misspecification issues. To draw the attention of researchers about its importance we include in all groups of regressions the first column with the misspecified equation.

Overall, our interpretations are based on the One-stage approach while SGMM and DFE are expected to provide a guideline over the direction of results.

6.2 Effects of Inter-industry Offshoring and Inshoring on TFP

From Table 6, we observe that an increase in downstream offshoring intensity faced by the focal firm will lead to a significantly positive increase in its productivity. The result is in line with Blalock and Veloso (2007), where import-driven technology transfers occur through vertical supply relationships. Given the construction of our proxies, we expect this productivity improvement to mainly be the result of increased competition from abroad. The reason is that in our proxies we consider only the category of products that are supplied to downstream firms and are also imported by the later. Therefore, any other category of products that could mainly generate technology and knowledge spillovers is not included.

Continuing, we observe that on average firms facing increased upstream offshoring intensity encounter a productivity disadvantage. This disadvantage could originate from the fact that firms cannot absorb the productivity advantage induced in upstream industries from offshoring

systematically with the relative position at which the supplier enters the production line. The nature of this 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. For the case of Belgium though we are not aware of any such elasticities and therefore cannot expect any exante results. But we expect to see that relatively upstream or downstream firms to vary on the way they absorb the inter-industry effects as they vary on their integration intensities.

[24]Relatively upstream includes industries with CPA:12,16,6,11,7,13,10 and relatively downstream industries with CPA:15,14,4,5,9,3,8. See Table 1 for correspondence with NACE 2-digit(rev.1).

[25]For SGMM we run 3 different regressions with instruments 1,2 or 3 lags of the endogenous variable to account for autocorrelation in the productivity innovation term as well. Results are not altered and hence report only the specification with one lag.

as they are not able to follow the rate of increase in the technology diffusion from better quality inputs and managerial practices from upstream. Therefore, on average firms will become sluggish and less productive in the sense that they increase their x-inefficiencies. But note that this is an average result over all manufacturing sectors.

Both upstream and downstream inshoring intensive sectors generate a positive and significant effect on productivity of the focal firms. Based on how the proxies are constructed, we are confident that for both channels, all the effect is due to indirect effects from upstream and downstream industries respectively i.e knowledge spillovers and not any direct effects i.e demand shock as in the downstream offshoring case. More precisely, as discussed in appendix A.2, any productivity effects to the focal firms from upstream and downstream firms inshoring will be embodied mainly in the products demanded and supplied.

Table 6, confirms the existence of the inter-industry effects from offshoring and inshoring on productivity. To be able to asses their importance on the productivity evolution of Belgian firms we provide their economic interpretation.[26] During the period 2002-2007 the average productivity of Belgian manufacturing firms increased by 0.34% from downstream offshoring, increased by 1.59% from upstream offshoring, increased 0.24% from downstream inshoring and increased by 1.14% from upstream inshoring. In total,we observe that on average Belgian manufacturing firms became more productive by approximately 3.3% from inter-industry offshoring and inshoring. In absolute terms this productivity enhancement is strong and becomes stronger when considered in relative terms. The later is confirmed from the top left graph of Figure 3 where we see that on average manufacturing firms experienced an increase of 1.7% in their TFP during 2002-2007. This suggests that productivity improvements from inter-industry linkages represent approximately two times the average TFP increase of Belgian manufacturing firms during 2002-2007.

From splitting our sample to high-medium and medium-low tech industries, it is clear from Table 7 that the later group is the one to rip the lions share of the benefits from inter-industry offshoring and inshoring by facing an overall productivity improvement of 3.1%.[27] On the other hand, high-medium tech industries appear to have a disadvantage from upstream inshoring that is weakly statistically significant (10%) and is of negligible economic effect. This result can be reconciled with the fact that RnD intensive industries have become relatively less fragmented over time (Fally, 2011).

From Table 8, we see that the the channels through which we get significant and positive results are for the relatively labor intensive industries. In total, we see that the relatively labor intensive industries will benefit from an average increase of 5.82% in their productivity from inter-industry offshoring and inshoring while the relatively capital intensive industries will face a decrease of 3.18% increase in their productivity. This places extra validity on the argument that labor intensive industries outsource more since decisions taken by suppliers are relatively more important while capital intensive industries are more integrated as they rely more on investment decisions take by headquarters.

Finally, we confirm the expected heterogeneity of results over the relative position of industries in the production line. Relatively upstream firms show an average productivity increase of 5.33% while relatively downstream firms an increase of 0.19%.

It is important to observe that the most significant and large in scale productivity effects are generated from the upstream linkages. The importance of those channels, is something not confirmed in the literature i.e in Javorcik (2004) MNC presence only in downstream industries could generate knowledge spillovers (backward linkages).

[26] We use estimated coefficients from the One-stage column and the absolute change from 2002 to 2006 for the respective proxies as in table 3. For 2002 to 2007 absolute changes in the respective proxies, results are of bigger magnitude.

[27] The linkages are the same as before, with downstream offshoring leading to an average productivity decrease of 0.04%, upstream offshoring to an increase of 1.42% , downstream inshoring to an increase of 0.34% and upstream inshoring to a 1.37% increase.

6.3 Effects of Inter-industry Offshoring and Inshoring to China on TFP

In the previous section we established the existence of downstream and upstream linkages through which offshoring and inshoring-driven productivity enhancements occur. In this section we apply the exact same procedure but now split our proxies to country of origin, China (CN) and rest of the world excluding China (excCN).[28] Note that in all regressions we include both parts of the split proxies CN and excCN. This is based on the idea that selection into importing features complementarity across markets because sourcing decisions generally interact through the cost function Antras et al. (2014).

From Table 10, we see that upstream offshoring to China leads to an average productivity increase of 0.5% respectively. This is the only statistically significant channel and represents approximately 30% of the increase in the average productivity of firms during 2002-2007. In absolute terms this productivity enhancement is considered small. In relative terms though, it can be argued that this increase is still very important for firms. The reason is that we consider one trading partner (China) that accounts to only a small fraction of Belgian trade that is EU-US oriented. Also, contrary to the majority of empirical studies that focus on developing economies, our results apply to a small open developed economy where inefficiencies are already reduced drastically and firms produce close to their production frontier. Therefore, any productivity enhancing activity will be marginal as it will also come up with a higher opportunity cost. This suggests that any productivity improvement from inter-industry linkages is vital for firms' planning and survival decisions especially in an environment where opportunities for productivity advancements are slim and expensive.

Comparing results from the previous section we observe that now the effects on productivity from upstream offshoring and downstream inshoring to China have for most of the cases opposite directions. This could be interpreted under the scope that different trading partners' characteristics generate heterogeneous effects (Chaney, 2008; Helpman et al., 2007; Manova and Zhang, 2012).[29]

As reported from Table 11 all the productivity gains are ripped from firms in medium-low tech industries with an overall average productivity gain of 0.67%. However, firms in high-medium tech industries seem to enjoy productivity gains of 6.4% from upstream offshoring that are statistically significant only at 10% and hence avoid to consider it as an economically significantly interpretable impact from inter-industry offshoring and inshoring to China.

Continuing, based on Table 12 we see that upstream offshoring to China is making on average firms in relatively labor intensive industries more productive by approximately 0.91% while relatively capital intensive industries receive a productivity disadvantage of -0.95%. On the other hand, relatively downstream or upstream industries do not exert any significantly interpretable impact on TFP from inter-industry linkages.

As already argued China's accession to WTO in 2001 can be considered as a semi-trade liberalisation event for Belgium. Since the end of 2001 Belgium-China's bilateral trade restrictions fell sharply leading to the consideration of China as a "new" trading partner for Belgium. This implies that China's accession to WTO, up to the extent that it was exogenous to the firm and not induced from any lobbying activities, led to an exogenous variation in trade statistics and in our case in the proxies of interest (see figure 2). Therefore we can argue that all productivity effects from inter-industry linkages are induced from this semi-trade liberalisation event. On average, Belgian firms benefited only from upstream offshoring to China as a result of opening up to trade with this "new" trade destination.

[28]Because of data restrictions China inherently includes Hong-Kong and Macao.

[29]For the rest of the proxies where trade excCN is considered, the effects on productivity follow the same direction as in the previous section.

6.4 Value Added Bias

Both theory and empirical research have reached a consensus on MNC firms being on average more productive compared to both domestic and exporting firms Melitz et al. (2004); Yeaple (2006). This is a standard selection effect originating from Melitz (2003) since more productive firms will become MNC's and will on average be more productive. In our estimations however, we identify a learning by being a MNC effect on TFP, expected to be positive and significant.[30] [31] However, this effect is insignificant and with uninterestingly low point estimates ranging from 0.9%-0.01% depending on the specification. (Run also a simple regression between TFP and MNC status to show that even the simple correlation vanishes.)

A possible explanation, is that the GNR estimation procedure corrects for "value added bias". This leads to less dispersed productivity estimates compared to estimation procedures based on value added production functions (see GNR). Intuitively, in the later case, variation in output includes both variation in productivity and excluded inputs i.e material. Given the assumption that productivity is positively correlated with material, an upward bias in the degree of productivity heterogeneity is expected. Under this spectrum, results for all point estimates are expected to be of lower magnitudes.

To get a more clear image of the bias we generate productivity estimates using the ACF two step value-added procedure as described in detail in Appendix C. In Figure 4, we plot the re-centered distributions of the log TFP's for GNR gross output and ACF value added procedures in each industry. From a visual inspection we can safely conclude that the later estimation procedure generates more heterogeneous and dispersed productivity estimates. In addition, from Figure 5 we erroneously conclude that the distribution of log productivities of MNC firms visually dominates the respective distribution of non-MNC's, something not apparent under the GNR gross output procedure. This is a strong sign that value-added bias is in motion making our estimates inconsistent.[32]

To test our concerns, we produce all results up to this point based on productivity estimates using ACF two step value-added procedure. Due to space constraints we report only table 14 and 15 that are directly comparable with table 6 and 10.[33]

First remark is that the correctly specified One-stage procedure as reported in the last column of each table fails to produce any significant results. Also, the magnitudes of the point estimates, are way off compared to the other closely related specifications (second and third column). This is puzzling to us as we expect results to at least be in line with the closest specification in column 2. We can safely assume that this erroneous outcome is most likely generated from the value added bias.

Second, by comparing the first three columns of table 14 and 15 with those of table 6 and 10 we observe that all point estimates are overestimated. This leads to erroneously economically interpretable effects from inter-industry offshoring and inshoring that are 3-10 percentage points higher in absolute values. Also, a learning by being MNC effect is significant and ranges from 1.5%-2.5%.

Overall, we get a clear sign that estimations using value added production functions suffer from serious bias as in GNR.

[30] This is the percentage increase in productivity due to being a MNC last period (see Aw et al. (2008); De Loecker (2013); Doraszelski and Jaumandreu (2013).

[31] As in Melitz (2003) and up to the extent that fixed costs for acquiring or being acquired by other domestic firms is higher (lower) than not, we expect the coefficients for SHH_BE and SUB_BE to be positive (negative) and strongly significant.

[32] To exclude the possibility that differences are not driven from the choice of production function, we also use GNR with a translog production function in order for productivities to be directly comparable. All remarks hold.

[33] For the rest of the cases results follow the same pattern and are available upon request.

7 Robustness

Results are robust to different production functions i.e Translog, Cobb-Douglas and 3rd order polynomial for both the output elasticity of the flexible input and constant of integration in the GNR, to different values for fixing the technical coefficient and making it varying, to possible omitted variable bias from not including intra-industry proxies, to various trimming methods, to timing assumption that labor faces adjustment costs but no adjustment lag and to firm fixed effects within the GNR procedure. See respective Tables 16-21

8 Conclusion

After a great amount of research in the trade literature over the growing importance of offshoring and in general the break down of the production value chain we would like to shift our interest to the importance of offshoring and inshoring via inter-industry linkages on firm productivity.

So far the literature has not paid any attention to the importance of such effects on the productivity of manufacturing firms. Our results confirm the existence and importance of such effects for the case of Belgium from 2002-2007. Also, China's accession to the WTO, considered as a quasi-natural event, allows us to argue that these productivity gains via inter-industry linkages can be induced from trade openness. We confirm that medium-low tech, labor intensive or relatively upstream industries manage to exploit these benefits mainly via upstream linkages. Finally, it is imperative to correct for value added bias and misspecification concerning the dynamic nature of productivity.

We should note though that due to data restrictions we do not try to recognise the exact mechanisms behind each channel that generate these effects i.e competition, quality standard discrepancies, managerial practices and organisational structures. We just give rise to the importance of such effects on the overall firm performance and how they can be linked to trade liberalisation events. It would also be misleading to give exact interpretations for these effects as our proxies are at the aggregate level and as proved from our analysis there is a lot of heterogeneity that needs to be exploited. This could give rise to new linkages that were not prevalent before. Therefore, we expect our analysis to cover the gaps in international trade literature and act as guidance for future research were more disaggregated data, ideally firm-level, will provide identification of the more precise impact on the firm level productivity.

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Appendices

A Definition and Measurement of Proxies

A.1 Offshoring

Based on the seminal work of Feenstra and Hanson (1996), *intra-industry* offshoring intensity is proxied as the share of imported intermediate inputs over total intermediate inputs used in the industry:

$$off_{jt} = \frac{MII_{jt}}{TII_{jt}} \tag{A.1}$$

where MII_{jt} stands for imported intermediate inputs, TII_{jt} for total non-energy intermediate inputs of industry j at time t.[34] Due to data limitations, our definition of offshoring also includes production transfers within multinationals (vertical FDI), where intermediate inputs flow between affiliated companies. For the computation of the proxies it is common in the literature to use the symmetric IO tables that in our case can be retrieved from the World Input-Output Database (WIOD).

The WIOD provide detailed enough information, to break down the proxies according to the partner country (origin) that we offshore to:

$$off_{jt}^{origin} = \frac{MII_{jt}^{origin}}{TII_{jt}} \tag{A.2}$$

where the index *origin*, refers to 40 foreign countries, one of which is considered as Rest of World (RoW).[35] By summing (A.2) across all countries we retrieve proxy (A.1).

The proxies up to now are not of any interest to us as extensive research on the *intra-industry* effects is already well documented and serve only for expositional reasons over the natural evolution for the construction of the proxies of interest in the next sections.

A.1.1 Downstream Offshoring

By relying on the above measure of offshoring though, we limit our attention on the effect of offshoring *within* the same industry. For example, the impact on firms in the Manufacture of Ruber and Plastics from offshoring. Apparently, this measure ignores the *inter-industry* effects. At time t, firms in the Manufacture of Ruber and Plastics supply their final output for intermediate input use to domestic firms in the Manufacture of Machinery and Equipment. At $t + 1$ the Manufacture of Machinery and Equipment decides to partly or holy offshore the intermediate inputs needed from the Manufacture of Ruber and Plastics . This change in the offshoring behaviour of firms in the downstream Manufacture of Machinery and Equipment is likely to impact the performance of firms in the Manufacture of Ruber and Plastics. The *industry-level* proxy that we construct in order to capture the effect transmitted to firms in the supplying industry from the offshoring activity undertaken by firms in downstream industries was first proposed by Merlevede and Michel (2013) and defined as downstream offshoring.

The proxy is computed using International Supply, International Use and WIOT tables from WIOD. It brings together both the links of domestic industries supplying intermediate input products to other domestic downstream industries and the offshoring activity for those products

[34] Feenstra and Hanson (1999), distinguish between narrow (intermediates from the same industry) and broad (all imported intermediates) offshoring. For the rest of the paper we use only the later case.

[35] Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China(includes Macao and Hong Kong), Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Korea, Malta, Mexico, Netherlands, Portugal, Poland, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Taiwan, Turkey, UK and USA.

from domestic downstream industries. This proxy will provide a linkage through which any change in the offshoring intensity of downstream firms will impact domestic suppliers. Define j for the focal industry, d for downstream industry and $P = (p^1, p^2, \ldots, p^N)$ as the set of all products p indexed by $n = 1, \ldots, N$ that are produced in the economy.

From the International Supply tables we can retrieve the output product mix of firms in industry j, $P_j^{SUP} \subset P$ i.e the final products produced by firms in industry j. Respectively, from the International Use tables, we get the product mix of intermediate input purchases by domestic downstream industry d that are also offshored, $P_d^{USE} \subset P$ i.e the products that firms in industry d supply as intermediate inputs from domestic industries and also offshore to foreign countries. All the final products produced by firms in industry j, purchased as intermediate inputs and offshored by firms in industries d are represented by the intersection of the two previous sets of products, $P_{jd} = P_j^{SUP} \cap P_d^{USE}$. Therefore, given the 59 product categories and 35 industries from the tables in the WIOD, P_{jd} will in some combinations of jd contain more than one product, giving us the opportunity to capture the importance of secondary output as well.[36]

Firms in downstream industries d choose between domestic sourcing or importing any of the intermediate inputs n. Hence, if for example d increasingly offshores product $p^n \subset P_{jd}$, then firms in industry j would face a demand shock. This offshoring intensity for each matched product p^n by each dowstream industry d is computed as in (A.1) from the International Use tables:

$$off_{dnt} = \frac{MII_{dnt}}{TII_{dnt}} \tag{A.3}$$

where MII_{dnt} is imported intermediate input n and TII_{dnt} total intermediate input n for industry d.

The extent to which imports of intermediate products n by downstream industry d affect focal industry j, is computed as a weighted sum of off_{dnt} for all products n that j supplies as intermediate inputs to downstream industries d and in their turn also offshore, P_{jd}:

$$\Phi_{jdt} = \sum_{p^n \subset P_{jd}} \delta_{jnt} off_{dnt} \tag{A.4}$$

where the weight $\delta_{jnt} = Y_{jnt} / \sum_{p^n \subset P_j^{SUP}} Y_{jnt}$, declares the relative importance of final product n for industry j. They are computed from the International Supply tables as the share of industry j's final product p^n over its output mix P_j^{SUP}.

As a final step, downstream offshoring for industry j, is defined as the weighted sum of Φ_{jdt} for all the downstream industries d that it supplies with intermediate inputs:

$$Down\_off_{jt} = \sum_{d \neq j} \theta_{jdt} \Phi_{jdt} \tag{A.5}$$

where the weight, $\theta_{jdt} = Y_{jdt} / \sum_d Y_{jdt}$ is computed from the WIOT and denotes the relative importance of the output supplied to downstream industry d over all downstream industries d.

Industries where $j = k$ are excluded, as they refer to *intra-industry* offshoring that is already captured from traditional offshoring measure off_{jt} (A.1). Also, θ_{jdt} is fixed to a value prior to the starting year of our estimation sample, i.e θ_{jd2000}. This way we eliminate distortion of relative magnitudes across time and across industries and bring exact identification of the

[36]There is no consensus in the literature over which sectors should be included in the measures. Our benchmark proxy will contain products from all sectors excluding:Agriculture, Hunting, Forestry and Fishing; Mining and Quarrying; Coke, Refined Petroleum and Nuclear Fuel; Electricity Gas and Water Supply; Construction; Hotels and Restaurants; Financial Intermediation; Public Admin. and Defence; Education; Health and Social Work;Other Community, Social and Personal Services; Private Households with Employed Persons. For robustness we employ alternative measures but they result in similar patterns.

downstream offshoring effects. In addition, we can more easily argue over the exogeneity of the proxy on the idiosyncratic error of the productivity estimates.

Overall, $Down\_off_{jt}^{fix\theta_{2000}}$ will be used as our baseline definition for downstream offshoring where higher values are interpreted as industry j facing higher downstream offshoring.[37]

Using WIOD tables we can further decompose the measure according to the origin of partner country that we offshore to. For this case, we break down off_{dnt} (A.3), to off_{dnt}^{origin}, where *origin*, represents any of the foreign countries where firms in industry d offshore product n to. Therefore, following the pre mentioned procedure we get for each *origin*:

$$Down\_off_{jt}^{origin} = \sum_{d \neq j} \theta_{jdt} \Phi_{jdt}^{origin} \tag{A.6}$$

By summing (A.6) across all *origin* we retrieve (A.5).

A.1.2 Upstream Offshoring

With downstream offshoring we capture the vertical supply linkages of *inter-industry* offshoring. Respectively, there could be vertical demand linkages that could allow these effects to be transmitted from the opposite direction. For example, if firm in the focal industry j demands intermediate inputs from firms in upstream industry u, we expect that a change in the offshoring behaviour of u will impact the performance of j. The mechanisms can include reduced cost of intermediate inputs sourced from low wage countries, higher quality standards, better management techniques, more efficient allocation of resources, reverse engineering, organisational restructuring, knowledge or R&D spillovers and international networking.

This "impact" that is generated from the offshoring activity of upstream industry u, is transferred via the production process to its final product(s) that are later on supplied as intermediate inputs to firms in industry j. Therefore, if for instance Belgian Manufacture of Wearing Apparel and Furs products is supplied part of its intermediate inputs from Belgian Manufacture of Leather and Leather products, and the later increasingly offshores to foreign countries, we would expect the Belgian Manufacture of Wearing Apparel and Furs to experience a productivity effect. The mechanisms could me more than one as described above and each one of them could lead to opposite direction effects. What we will measure is the overall direction and magnitude of this effect.

We will define this demand linkage of the *inter-industry* effect as upstream offshoring. A proxy to quantify it, as far as we are concerned, is proposed for the first time and the rationale behind it is similar to that of downstream offshoring:

$$Up\_off_{jt} = \sum_{u \neq j} \zeta_{jut} \Psi_{jut} \tag{A.7}$$

where $\Psi_{jut} = \sum_{p^n \subset P_{ju}} \gamma_{jnt} off_{unt}$, defines the extent to which the offshoring activity of upstream industry u affects industry j.[38] The weight γ_{jnt}, is computed from the International Use tables and captures the relative importance of the use of intermediate product n over all intermediate inputs used from industry j. The technical coefficient ζ_{jut}, is computed from the WIOT and refers to the relative importance of upstream industry u over all domestic upstream industries u that j is supplied from.[39]

Upstream offshoring can be further decomposed by partner country that we offshore to:

$$Up\_off_{jt}^{origin} = \sum_{u \neq j} \zeta_{jut} \Psi_{jut}^{origin} \tag{A.8}$$

[37]For brevity, we suppress the index indicating that we fix θ_{2000} for the rest of the cases.

[38]The product mix P_{ju}, will now contain products that are used as intermediates by industry j, P_j^{USE}, and products that are offshored by industry u, P_u^{USE}. Hence, we exclude the effect from the products that are offshored by u and are not used by downstream industry j.

[39]For identification reasons we fix ζ_{jut} to year 2000 as before.

By summing (A.8) across all *origin* we retrieve (A.7).

A.2 Inshoring

For a holistic assessment of the *inter-industry* effects of internationalization it would be inappropriate to restrict our attention only to offshoring. Therefore, we should also examine the mirror dimension of offshoring that is not yet analysed in depth. We refer to this mirror action as *inshoring* and define it as the export of final output that will be used for intermediate input usage to both affiliated and unaffiliated firms in a foreign country.[40]

We will proxy inshoring intensity in close relation to Feenstra and Hanson (1996):

$$in_{jt} = \frac{XY_{jft}}{TY_{jt}} \tag{A.9}$$

where XY_{jft} is the share final output from industry j that is exported only for intermediate input usage, TY_{jt} is industry j's final output that is supplied only for intermediate input usage to both foreign and domestic firms. The WIOD provides time-series of world input-output tables for forty countries worldwide, allowing us to have a complete picture of the amount of intermediate inputs exported at the industry level across countries. Contrary to offshoring, we cannot observe the inshoring intensity for the RoW country (as defined in WIOD) and therefore assume that the pre mentioned 40 countries will constitute a good proxy for total worldwide inshoring intensity.

Inshoring can be further decomposed by the destination country that we offshore to:

$$in_{jt}^{origin} = \frac{XY_{jt}^{origin}}{TY_{jt}} \tag{A.10}$$

By summing (A.10) across all *origin* we retrieve (A.9).

A.2.1 Downstream Inshoring

For *inter-industry* effects of inshoring we will introduce for the first time proxies in complete analogy to *inter-industry* offshoring. For instance, suppose that the Manufacture of Computer and Related Services supplies with intermediate inputs the downstream Manufacture of Office Machinery and Computers. The later starts to increasingly export its final product to other firms only for intermediate input usage i.e inshoring. This increase in the inshoring intensity from the downstream Manufacture of Office Machinery and Computers is likely to have an effect on the productivity of the supplying Manufacture of Computer and Related Services. The mechanisms as in the upstream offshoring case, could be multiple such as the need for increased quality of the intermediate input to meet exporting standards or innovation and knowledge spillovers.

We will define this *inter-industry* effect as downstream inshoring:

$$In\_down_{jt} = \sum_{d \neq j} \theta_{jdt} \Lambda_{jdt} \tag{A.11}$$

where $\Lambda_{jdt} = \sum_{p^n \subset P_{jd}} \delta_{jdt} in_{dnt}$, defines the extent to which the inshoring activity of downstream industry d affects industry j.[41] As mentioned before, in_{dnt} proxies the inshoring intensity of industry d for product n and is calculated from the International Use tables, i.e the share of

[40]The term was initially inspired by Slaughter (2004) that used "insourcing" as the converse dimension of outsourcing including only foreign direct investments, but was coined by Liu and Trefler (2008) that used it for the case of unaffiliated companies and its effect on labor.

[41]The product mix P_{jd} will now contain products that are used as intermediates by industry j, P_j^{USE}, and products that are inshored by industry d, P_d^{USE}.

product n exported by industry d and used as intermediate input. The weights δ_{jnt} and θ_{jdt} are defined as above.[42]

Downstream inshoring can be further decomposed by partner country that we inshore from:

$$In\_down_{jt}^{origin} = \sum_{d \neq j} \theta_{jdt} \Lambda_{jdt}^{origin} \tag{A.12}$$

By summing (A.12) across all *origin* we retrieve (A.11).

A.2.2 Upstream Inshoring

Upstream inshoring will encapsulate the *inter-industry* effects of inshoring via demand linkages:

$$In\_up_{jt} = \sum_{u \neq j} \zeta_{jut} \Xi_{jut} \tag{A.13}$$

where $\Xi_{jut} = \sum_{p^n \subset P_{ju}} \gamma_{jnt} in_{unt}$, defines the extent to which the inshoring activity of upstream industry u affects focal industry j. The weights γ_{jnt} and ζ_{jut} are computed as before.[43]

Upstream inshoring can be further decomposed by partner country that we inshore from:

$$In\_up_{jt}^{origin} = \sum_{u \neq j} \zeta_{jut} \Xi_{jut}^{origin} \tag{A.14}$$

By summing (A.14) across all *origin* we retrieve (A.13).

[42]For identification reasons we fix θ_{jdt} to year 2000.

[43]For identification reasons we fix ζ_{jut} to year 2000.

B GNR Two-step Estimation Procedure

This section serves as a short description of the steps and assumptions undertaken for the seminal estimation procedure proposed by GNR. For a full and complete overview of the estimation procedure refer to Gandhi et al. (2012).

This case considers the classic environment of perfect competition in input and output markets. Concerning the timing assumptions, capital is a quasi-fixed factor and therefore chosen one year prior to the realisation of productivity. Contrary to the majority of literature, we treat labor as a dynamic input chosen one year before the productivity realisation, just like capital. Rigidities in Belgian labor market, induce high labor adjustment frictions. This is translated to an adjustment lag resulting in a year lag between the choice of labor and its realisation.[44] The only flexible input in our specification is material, assumed to freely adjust in each period (variable) and have no dynamic implications (static).

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

$$P_t^M = P_t \frac{\partial}{\partial m_t} F_t(L_{it}, K_{it}, M_{it}) \mathrm{e}^{\omega}_{it} \mathcal{E} \tag{B.1}$$

where P_t^M and P_t is 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 over it that are similar across firms, $\mathcal{E} = E(\mathrm{e}^{\epsilon_{it}})$.[45] It is important to account and correct for this term since ignoring it, i.e. $\mathcal{E} = 1$, inherently implies that we move from the mean to the median central tendency of $\mathrm{e}^{\epsilon_{it}}$ (see Goldberger (1968)).

Combining (B.1) with production function (2) and re-arranging terms, we retrieve a share equation:

$$s_{it} = ln(G_t(L_{it}, K_{it}, M_{it}) + ln\mathcal{E} - \epsilon_{it} \tag{B.2}$$

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

B.1 Step One

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

$$G_t(L_{it}, K_{it}, M_{it)}\mathcal{E} = \sum_{r_l + r_k + r_m \leq r} \gamma'_{r_l, r_k, r_m} l_{it}^{r_l} k_{it}^{r_k} m_{it}^{r_m},\ with\ \ r_l, r_k, r_m \geq 0 \tag{B.3}$$

approximated by a polynomial series estimator or order r. From this step we non-parametrically identify ϵ_{it} (hence $\mathcal{E}$) and the output elasticity of the flexible input material.

B.2 Step Two

By integrating up the output elasticity of the flexible input:

$$\int \frac{G_t(L_{it}, K_{it}, M_{it})}{M_{it}} dM_{it} = lnF_t(L_{it}, K_{it}, M_{it}) + \mathcal{B}_t(L_{it}, K_{it}) \tag{B.4}$$

[44] For similar treatment see De Loecker et al. (2014); Konings and Vanormelingen (2009). In the robustness section we provide results over alternative definitions of adjustment frictions such as adjustment costs (hiring/firing costs).

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

we non-parametrically identify the production function up to an unknown constant of integration. By differencing it with the production function (2) we retrieve the following equation for productivity:

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

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

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

To proceed we exploit the assumption over the law of motion for productivity. Similar to the seminal work of OP, an exogenous first order Markov process is followed, $\omega_{it} = g_{it}(\omega_{it-1}) + \xi_{it}$. However, to accommodate concerns raised by Aw et al. (2008); De Loecker (2013), exogeneity is relaxed. Lagged and observable variables $s_{it-1} = (MNC_{it-1}, SUB_{it-1}, SHH_{it-1})$ are allowed to affect current productivity outcomes, $\omega_{it} = g_{it}(\omega_{it-1}, s_{it-1}) + \xi_{it}$.[46] Continuing from the previous step we can now express the innovation to productivity ξ_{it} as a function of the parameters of the constant of integral to be estimated $\xi_{it}(\alpha)$, by non parametrically regressing $\omega_{it}(\alpha)$ on $g_{it}(\omega_{it-1}(\alpha), s_{it-1})$.

The second step proceeds with a standard GMM. The moments used are $E(\xi_{it} n_{it}) = 0$. The orthogonality conditions, depend on the timing assumptions of inputs. For the case of a polynomial of degree two:

$$n_{it} = (k_{it}, l_{it}, k_{it}^2, l_{it}^2, k_{it} l_{it}) \tag{B.7}$$

where capital and labor are quasi-fixed inputs decided one year before and thus orthogonal to the innovation of productivity.

For a polynomial of degree two for both (B.3) and (B.6) the estimated gross output production function is:

$$\begin{aligned} y_{it} = \{&\gamma_0 + \gamma_k k_{it} + \gamma_l l_{it} + \frac{\gamma_m}{2} m_{it} + \gamma_{ll} l_{it}^2 + \gamma_{kk} k_{it}^2 + \frac{\gamma_{mm}}{3} m_{it}^2 \\ &+ \gamma_{lk} l_{it} k_{it} + \gamma_{lm} l_{it} m_{it} + \frac{\gamma_{lm}}{2} l_{it} m_{it} + \frac{\gamma_{km}}{2} k_{it} m_{it}\} \ m_{it} \\ &- \alpha_l l_{it} - \alpha_k k_{it} - \alpha_{ll}^2 l_{it} - \alpha_{kk}^2 k_{it} + \omega_{it} + \epsilon_{it} \end{aligned} \tag{B.8}$$

Using estimates of the production function coefficients $\hat{\gamma}$ and $\hat{\alpha}$ at the CPA industry level, we retrieve productivity estimates $\hat{\omega_{it}}$ for firm i in industry j at time t from equation (B.5).

[46] Exploiting richness of the data we define variables that indicate if firms control at least one subsidiary with ownership greater than zero (SUB) or are controlled by at least one firm with ownership greater than zero (SHH).

C ACF Two-step Estimation Procedure

ACF two step estimation procedure controls for collinearity problems encountered in LP. Assumptions imposed about competition and timing of firm's decisions are as in the previous section. First, we consider a log additive in the Hicks-neutral productivity term for a value added production function, $VA_{it} = Y_{it} - M_{it} = F(K_{it}, L_{it})e^{\omega_{it}}$. A translog specification is considered based on its high application frequency in empirical research. In logs, the production function to be estimated for each CPA industry is of the following form:

$$va_{it} = \gamma_k k_{it} + \gamma_l l_{it} + \gamma_{kk} k_{it}^2 + \gamma_{ll} l_{it}^2 + \gamma_{kl} k l_{it} + \omega_{it} + \epsilon_{it} \tag{C.1}$$

where va_{it}, k_{it}, l_{it} are log values of double deflated value added, deflated capital and l_{it} is the log of total number of employees for firm i at time t.

Conditional on the state variables of the firm and other firm characteristics, the firm's static profit maximization yields material input demand $m_{it} = m(l_{it}, k_{it}, m_{it}, z_{it})$, where z_{it} is a vector of age, region, MNC, SHH, SUB status and wages.[47] To control for unobserved productivity ω_{it}, we use the inverted intermediate input demand $\omega_{it} = m^{-1}(x_{it}, z_{it})$. To approximate the later, we use a third-order polynomial of x_{it} while z_{it} is introduced additively in order to restrict the parameter space that we search over. Also, time dummies are included additively to control for time variant shocks common to all firms.

First stage regression $y_{it} = \phi(l_{it}, k_{it}, m_{it}, z_{it}) + \epsilon_{it}$, delivers a measure of output purged from ex-post shocks and measurement errors to output, $\hat{\phi}_{it}$. From this we can obtain productivity as a function of the production function parameters γ to be estimated:

$$\omega_{it}(\gamma) = \hat{\phi}_{it} - x_{it}\gamma \tag{C.2}$$

where $x_{it} = (l_{it}, k_{it})$. As before, the law of motion for productivity is $\omega_{it} = g_{it}(\omega_{it-1}, s_{it-1}) + \xi_{it}$. Continuing from the previous step we express the innovation to productivity as a function of the production function parameters to be estimated $\xi_{it}(\gamma)$, by non parametrically regressing ω_{it} on $g_{it}(\omega_{it-1}, s_{it-1})$.

In the second step the coefficients of the production function are estimated with a standard GMM. The moments used are $E(\xi_{it} n_{it}) = 0$. Orthogonality conditions depend on the timing assumptions of inputs:

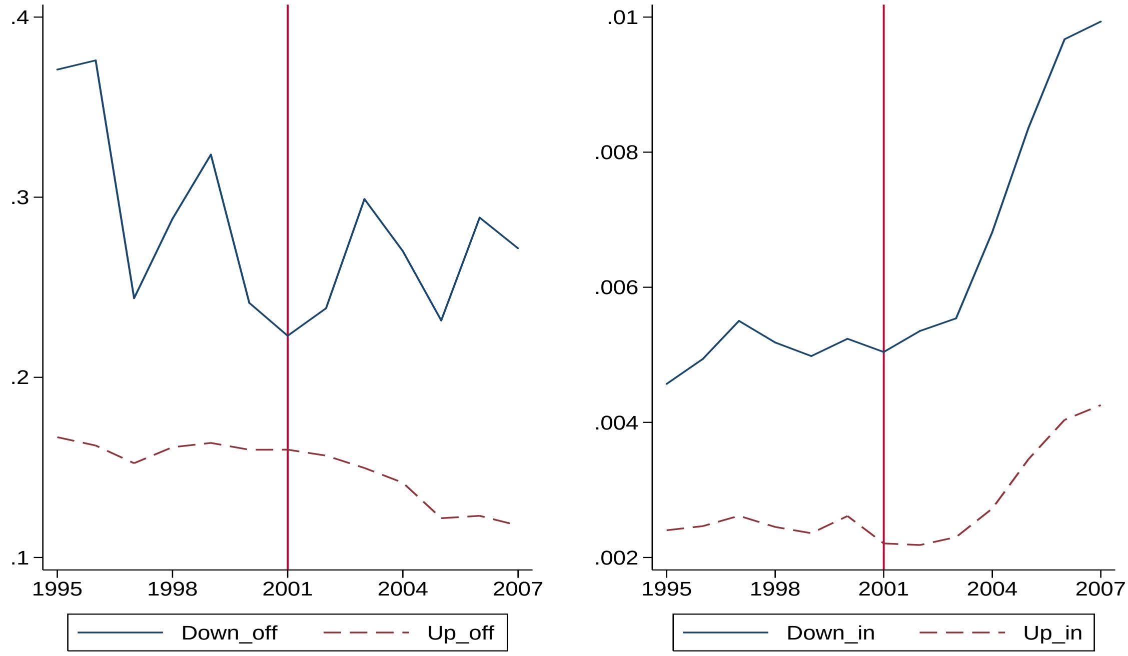
$$n_{it} = (k_{it}, l_{it}, k_{it}^2, l_{it}^2, k_{it} l_{it}) \tag{C.3}$$

where capital and labor are quasi-fixed inputs decided one year before and thus orthogonal to the innovation of productivity. Using estimates of the production function coefficients $\hat{\gamma}$ at the CPA industry level, we retrieve productivity estimates $\hat{\omega_{it}}$ for firm i in industry j at time t from equation (C.1).

[47] Richness of the data allows us to define variables that indicate if firms control at least one subsidiary with ownership greater than zero (SUB) or are controlled by at least one firm with ownership greater than zero (SHH).

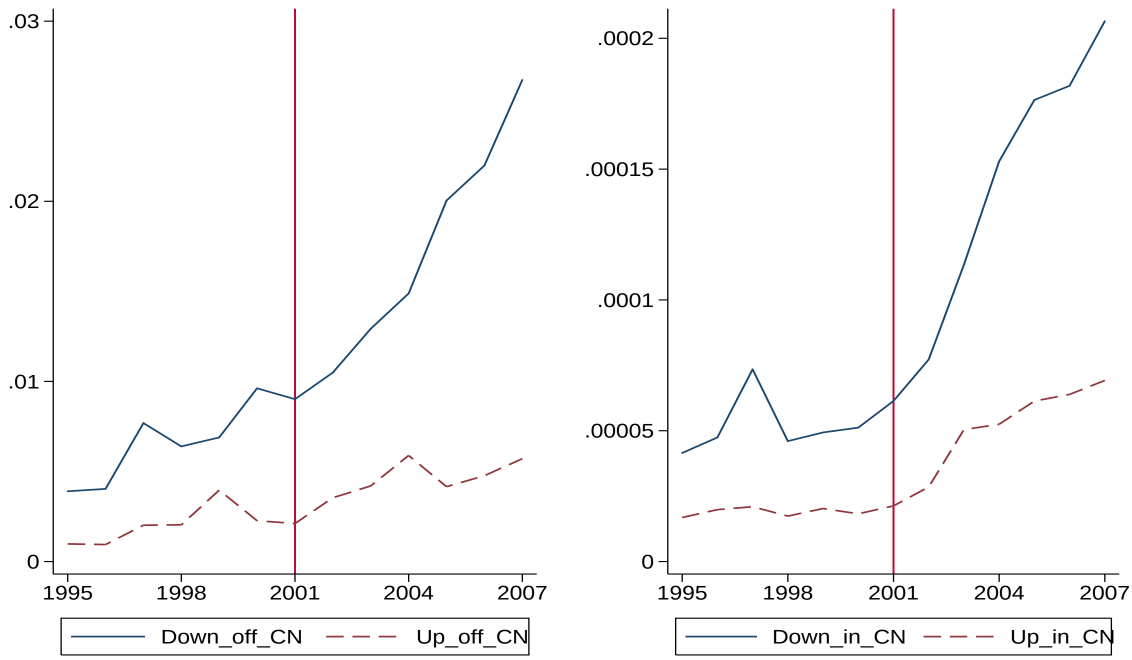
D Figures and Tables

Figure 1: Inter-industry offshoring and inshoring (annual averages across industries)



Source: Own calculations using World Input Output Database (WIOD)

Figure 2: Inter-industry offshoring and inshoring to China (annual averages across industries)



Source: Own calculations using World Input Output Database (WIOD)

Figure 3: Evolution of log of annual averages of TFP levels, by industry groups

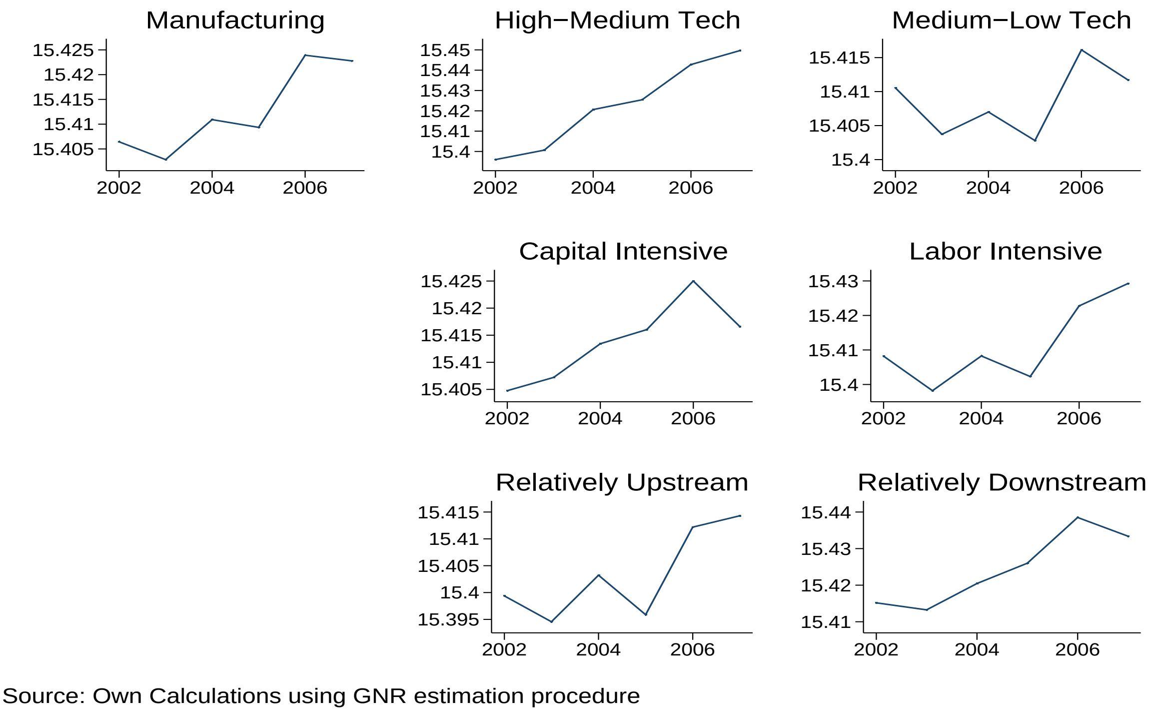


Figure 4: Distribution of log TFP by CPA industries

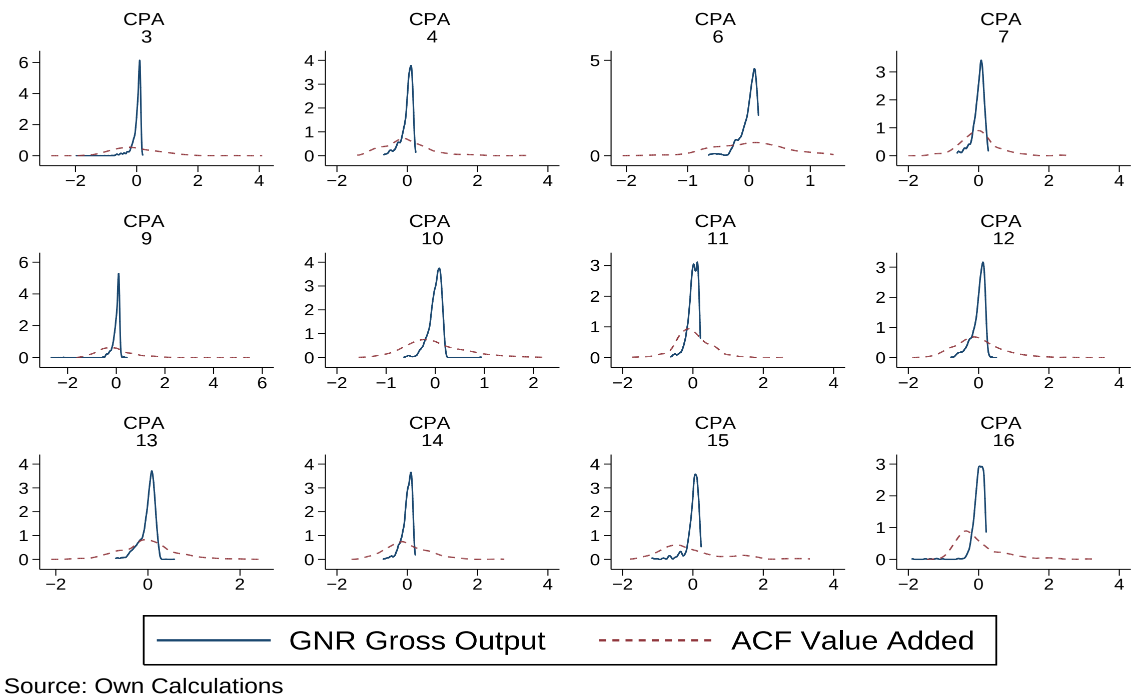
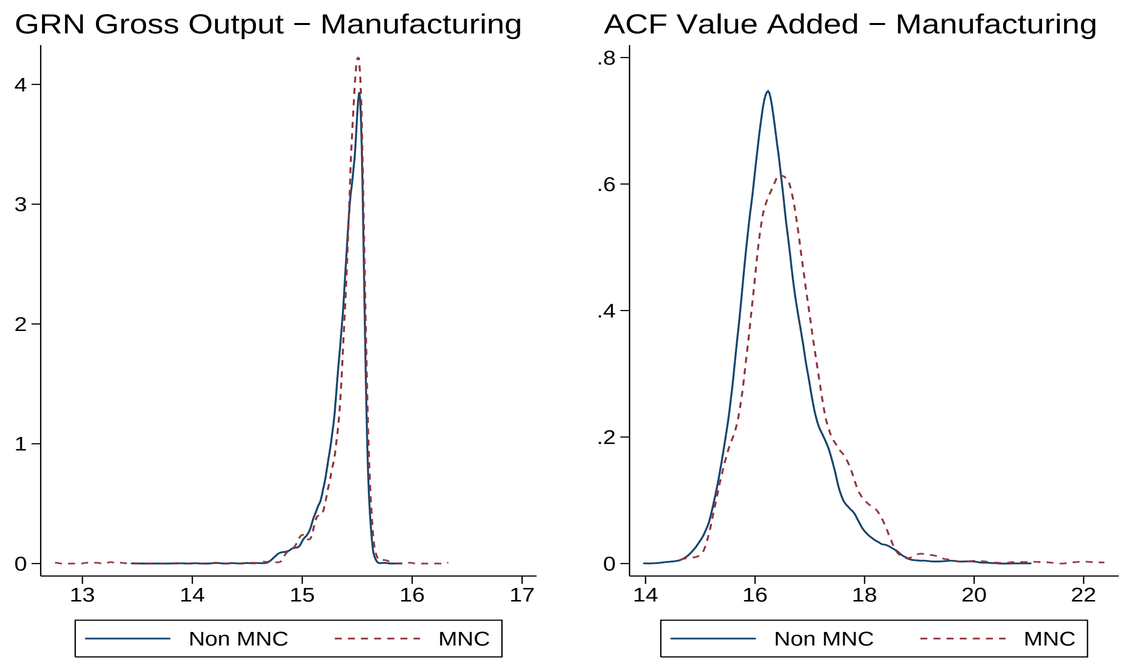


Figure 5: Distribution of log TFP by MNC status for manufacturing sector



Source: Own Calculations

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

CPA	NACE	Description
3	15t16	Manufacture of Food, Beverages and Tobacco
4	17t18	Manufacture of Textiles and Textile Products
5	19	Manufacture of Leather, Leather and Footwear
6	20	Manufacture of Wood and Products of Wood and Cork
7	21t22	Manufacture of Pulp, Paper, Printing and Publishing
8	23	Manufacture of Coke, Refined Petroleum and Nuclear Fuel Products
9	24	Manufacture of Chemicals and Chemical Products
10	25	Manufacture of Rubber and Plastic products
11	26	Manufacture of Other Non-Metallic Mineral Products
12	27t28	Manufacture of Basic Metals And Fabricated Metal Products
13	29	Manufacture of Machinery and Equipment n.e.c.
14	30t33	Manufacture of Electrical and Optical Equipment
15	34t35	Manufacture of Transport Equipment
16	36t37	Manufacture of Manufacturing, n.e.c.;Recycling

Table 2: Firm-level data

	Obs.	Mean	St.Dev.	Min	p25	p50	p75	Max
Operating Revenue	15496	52559	217558	124	7092	13652	31992	5802343
Tang Fixed Assets	15496	6711	28297	.25	525	1590	4302	814574
Material Costs	15496	31514	150392	11	3249	7175	17721	5076978
Employee Costs	15496	7188	24217	45	1179	2263	5071	675651
Nr of Employees	15496	132	359	2	26	50	110	8146
Average Wage	15496	49304	19406	15000	38415	44884	55250	486333
MNC	15496	.15	.35	0	0	0	0	1

Notes: Firm-level data from Amadeus dataset for 2765 Belgian manufacturing firms from 2002 to 2007. Operating Revenue, Tangible Fixed Assets, Material costs and Employee Costs are in thousand of Euro.

Table 3: Inter-industry offshoring and inshoring proxies

	Doff	Uoff	Din	Uin	Doff_CN	Uoff_CN	Din_CN	Uin_CN
2002	0.23836	0.15657	0.00535	0.00218	0.01049	0.00354	0.00008	0.00003
2003	0.29898	0.14970	0.00554	0.00230	0.01293	0.00420	0.00011	0.00005
2004	0.27005	0.14155	0.00682	0.00272	0.01488	0.00589	0.00015	0.00005
2005	0.23157	0.12181	0.00836	0.00345	0.02004	0.00416	0.00018	0.00006
2006	0.28871	0.12314	0.00967	0.00404	0.02199	0.00477	0.00018	0.00006
2007	0.27165	0.11780	0.00993	0.00426	0.02674	0.00571	0.00021	0.00007
D.(2007-2002)	0.03328	-0.03877	0.00458	0.00207	0.01625	0.00217	0.00013	0.00004
D.(2006-2002)	0.05035	-0.03343	0.00432	0.00185	0.01149	0.00122	0.00010	0.00004

Notes: Variables Doff, Uoff, Din, Uin, Doff_CN, Uoff_CN, Din_CN and Uin_CN represent downstream offshoring, upstream offshoring, downstream inshoring, upstream inshoring, downstream offshoring to China, upstream offshoring to China, downstream inshoring from China and upstream inshoring from China respectively. Each cell reports annual averages over manufacturing sector. The last two rows report the difference between values in 2007 and 2002.

Table 4: Output elasticities by CPA industries

		GNR				ACF Value added			ACF Gross output			
CPA	Obs.	$\hat{\theta}_k$	$\hat{\theta}_l$	$\hat{\theta}_m$	RTS	$\hat{\theta}_k$	$\hat{\theta}_l$	RTS	$\hat{\theta}_k$	$\hat{\theta}_l$	$\hat{\theta}_m$	RTS
3	2504	0.125	0.276	0.590	0.990	0.221	0.718	0.939	0.110	0.216	0.676	1.003
4	1225	0.062	0.331	0.547	0.941	0.141	0.701	0.842	0.061	0.237	0.687	0.985
6	386	0.100	0.274	0.552	0.925	0.228	0.682	0.910	0.053	0.198	0.738	0.989
7	1568	0.059	0.497	0.430	0.986	0.111	0.861	0.972	0.013	0.392	0.578	0.983
9	1521	0.127	0.380	0.503	1.011	0.238	0.789	1.027	0.088	0.335	0.624	1.048
10	749	0.112	0.390	0.518	1.020	0.181	0.787	0.968	0.066	0.283	0.636	0.985
11	1222	0.110	0.358	0.482	0.950	0.262	0.703	0.966	0.106	0.276	0.622	1.004
12	2712	0.087	0.366	0.503	0.956	0.150	0.717	0.868	0.067	0.313	0.583	0.963
13	1302	0.038	0.391	0.498	0.928	0.111	0.789	0.901	0.036	0.323	0.610	0.968
14	1244	0.052	0.449	0.481	0.982	0.105	0.879	0.984	0.034	0.362	0.621	1.017
15	371	0.076	0.338	0.582	0.996	0.187	0.758	0.944	0.056	0.283	0.678	1.018
16	692	0.035	0.318	0.550	0.903	0.188	0.602	0.790	0.044	0.232	0.712	0.989

Notes: Average of estimated output elasticities with respect to each factor of production for all firms in each CPA industry. RTS represents the average returns to scale.

Table 5: Upstreamness measure

Production Line Position	CPA	Mean	2002	2003	2004	2005	2006	2007
Relatively Downstream	8	2.38	2.83	1.32	2.29	2.38	2.68	2.80
	3	2.48	2.42	2.30	2.25	2.51	2.60	2.78
	9	2.63	2.87	2.61	2.59	2.53	2.57	2.59
	5	2.66	2.82	2.64	2.65	2.58	2.64	2.63
	4	2.70	2.99	2.83	2.73	2.50	2.58	2.55
	14	2.81	3.05	2.81	2.76	2.76	2.78	2.68
	15	2.83	2.90	2.70	2.65	2.95	2.84	2.92
Relatively Upstream	10	2.83	3.17	2.94	2.76	2.66	2.73	2.70
	13	2.83	3.09	2.95	2.95	2.62	2.69	2.68
	7	2.96	3.24	3.17	3.13	2.72	2.75	2.76
	11	2.97	3.11	3.02	3.00	2.87	2.94	2.89
	6	3.11	3.19	3.10	3.06	3.08	3.11	3.15
	16	3.15	3.38	3.23	3.19	3.03	3.12	2.92
	12	3.53	3.85	3.69	3.66	3.42	3.39	3.20

Notes: Upstreamness measure is computed as in Antràs et al. (2012); Fally (2011) using WIOT dataset. Mean represents the mean value from 2002 to 2007 for each industry and is used to rank industries on their relative position in the production line.

Table 6: Effects of inter-industry offshoring and inshoring on TFP

	FD	DFD	SGMM	One-StageFE
LaglnTFP		0.921***	0.986***	0.933***
		(0.023)	(0.013)	(0.012)
Lagoffdown	-0.015	0.067***	0.109***	0.067***
	(0.012)	(0.010)	(0.012)	(0.012)
Lagoffup	-0.405***	-0.394***	-0.400***	-0.474***
	(0.093)	(0.062)	(0.109)	(0.067)
Lagindown	1.248***	0.571***	0.426**	0.561***
	(0.225)	(0.124)	(0.197)	(0.180)
Laginup	-0.684	6.356***	10.275***	6.161***
	(1.243)	(0.845)	(1.671)	(1.012)
LagSHHBE	-0.017**	-0.001	-0.002	-0.000
	(0.007)	(0.002)	(0.004)	(0.001)
LagSUBBE	0.009	-0.000	-0.004	0.001
	(0.008)	(0.001)	(0.005)	(0.004)
LagMNC	0.003	0.002	0.006	0.000
	(0.009)	(0.002)	(0.006)	(0.003)
Observations	15496	15496	15496	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 7: Effects of inter-industry offshoring and inshoring on TFP (High-Medium and Medium-Low Tech Industries)

	High-Medium Tech				Medium-Low Tech			
	FD	DFD	SGMM	One-Stage	FD	DFD	SGMM	One-Stage
LaglnTFP		0.908***	0.940***	0.927***		0.926***	0.996***	0.926***
		(0.016)	(0.019)	(0.017)		(0.018)	(0.006)	(0.020)
Lagoffdown	0.141***	0.044	-0.036	0.043	-0.070***	0.062***	0.127***	0.066***
	(0.031)	(0.041)	(0.065)	(0.106)	(0.014)	(0.011)	(0.017)	(0.012)
Lagoffup	-1.387***	-0.412	0.299	-0.558	-0.103	-0.415***	-0.585***	-0.487***
	(0.256)	(0.276)	(0.426)	(0.440)	(0.087)	(0.068)	(0.118)	(0.083)
Lagindown	-46.941***	-31.352**	-30.636*	-22.194	2.353***	0.513***	-0.022	0.514**
	(12.996)	(12.652)	(17.928)	(16.035)	(0.269)	(0.127)	(0.227)	(0.212)
Laginup	3.410	11.420***	10.322***	10.459*	5.929***	4.829***	5.752***	4.913**
	(2.242)	(2.054)	(4.000)	(5.579)	(1.671)	(1.023)	(2.085)	(2.189)
LagSHHBE	-0.008	0.002	0.007	0.002	-0.020***	-0.003*	-0.006	-0.001
	(0.012)	(0.003)	(0.009)	(0.004)	(0.007)	(0.001)	(0.005)	(0.002)
LagSUBBE	0.016	0.003	-0.014	0.002	0.007	-0.001	-0.005	-0.000
	(0.017)	(0.003)	(0.012)	(0.009)	(0.009)	(0.002)	(0.006)	(0.002)
LagMNC	0.005	0.004	0.009	0.005	0.001	0.001	0.007	-0.002
	(0.014)	(0.004)	(0.010)	(0.005)	(0.012)	(0.003)	(0.007)	(0.003)
Observations	4438	4438	4438	3650	11058	11058	11058	9081

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 8: Effects of inter-industry offshoring and inshoring on TFP (Capital and Labor Intensive Industries)

	Capital Intensive				Labor Intensive			
	FD	DFD	SGMM	One-Stage	FD	DFD	SGMM	One-Stage
LaglnTFP		0.935***	1.002***	0.950***		0.903***	0.961***	0.923***
		(0.011)	(0.004)	(0.015)		(0.028)	(0.020)	(0.015)
Lagoffdown	0.008	0.019	0.053***	0.017	0.117***	0.073***	0.051	0.092***
	(0.016)	(0.013)	(0.019)	(0.020)	(0.022)	(0.024)	(0.034)	(0.024)
Lagoffup	-0.747***	0.077	0.376	0.046	-1.264***	-0.288***	0.075	-0.343***
	(0.264)	(0.241)	(0.326)	(0.319)	(0.136)	(0.104)	(0.197)	(0.112)
Lagindown	12.535	-74.509***	-71.048***	-60.365***	0.071	0.590***	0.624**	0.626**
	(10.352)	(11.480)	(14.183)	(14.392)	(0.243)	(0.138)	(0.254)	(0.302)
Laginup	12.840***	14.147***	13.039***	11.560***	-15.560***	5.905***	8.038***	6.825***
	(1.552)	(1.650)	(1.968)	(1.947)	(2.136)	(1.453)	(2.706)	(1.676)
LagSHHBE	-0.013	-0.002	-0.004	-0.001	-0.023***	-0.001	0.002	0.000
	(0.009)	(0.002)	(0.007)	(0.003)	(0.008)	(0.002)	(0.005)	(0.002)
LagSUBBE	-0.001	0.001	-0.002	0.003	0.025***	-0.001	-0.001	-0.002
	(0.012)	(0.002)	(0.007)	(0.003)	(0.010)	(0.002)	(0.011)	(0.002)
LagMNC	-0.002	0.003	-0.000	-0.000	0.008	0.001	-0.001	0.003
	(0.014)	(0.003)	(0.008)	(0.005)	(0.011)	(0.003)	(0.011)	(0.004)
Observations	7950	7950	7950	6534	7546	7546	7546	6197

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 9: Effects of inter-industry offshoring and inshoring on TFP (Relatively Upstream and Downstream Industries)

	Relatively Upstream				Relatively Downstream			
	FD	DFD	SGMM	One-Stage	FD	DFD	SGMM	One-Stage
LaglnTFP		0.913***	0.992***	0.921***		0.927***	0.953***	0.936***
		(0.036)	(0.010)	(0.016)		(0.020)	(0.015)	(0.016)
Lagoffdown	-0.058***	0.059***	0.082***	0.056***	0.087***	0.090***	0.038	0.090
	(0.015)	(0.012)	(0.017)	(0.014)	(0.016)	(0.021)	(0.029)	(0.071)
Lagoffup	-0.956***	-1.004***	-0.527**	-1.117***	-0.526***	-0.337***	0.005	-0.374
	(0.171)	(0.124)	(0.209)	(0.149)	(0.116)	(0.083)	(0.150)	(0.244)
Lagindown	0.777***	-0.056	-0.063	-0.040	10.168	-2.650	-24.946	5.013
	(0.239)	(0.153)	(0.289)	(0.213)	(14.360)	(12.609)	(17.091)	(28.740)
Laginup	-5.489***	5.559***	4.348*	6.434***	10.460***	14.689***	19.057***	13.852***
	(1.784)	(1.304)	(2.561)	(1.569)	(2.306)	(1.699)	(2.914)	(4.726)
LagSHHBE	-0.016**	-0.001	-0.006	0.000	-0.018*	-0.002	0.000	-0.002
	(0.008)	(0.002)	(0.006)	(0.003)	(0.009)	(0.002)	(0.007)	(0.006)
LagSUBBE	0.021**	0.001	-0.004	0.001	-0.005	-0.001	-0.004	-0.002
	(0.008)	(0.002)	(0.009)	(0.002)	(0.014)	(0.002)	(0.008)	(0.014)
LagMNC	0.009	0.001	-0.003	0.002	-0.003	0.002	0.014	0.002
	(0.013)	(0.003)	(0.007)	(0.003)	(0.013)	(0.003)	(0.011)	(0.007)
Observations	8631	8631	8631	7085	6865	6865	6865	5646

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 10: Effects of inter-industry offshoring and inshoring to China on TFP

	FD	DFD	SGMM	One-Stage
LaglnTFP		0.920***	0.970***	0.933***
		(0.023)	(0.016)	(0.014)
LagoffdownCN	-0.364	-0.429**	-0.354	-0.508
	(0.292)	(0.179)	(0.277)	(0.325)
LagoffupCN	3.002**	3.240***	4.355***	4.121***
	(1.169)	(1.015)	(1.314)	(0.998)
LagindownCN	-142.645***	-4.161	14.421	-2.581
	(17.740)	(12.524)	(18.432)	(22.946)
LaginupCN	8.437	13.441	48.326*	13.376
	(18.413)	(20.466)	(27.079)	(37.138)
LagSHHBE	-0.017**	-0.001	-0.004	-0.000
	(0.007)	(0.002)	(0.004)	(0.002)
LagSUBBE	0.009	-0.000	-0.002	0.001
	(0.008)	(0.001)	(0.005)	(0.003)
LagMNC	0.003	0.002	0.000	0.000
	(0.009)	(0.002)	(0.007)	(0.004)
LagoffdownexcCN	-0.109**	0.099**	0.229***	0.107**
	(0.055)	(0.040)	(0.075)	(0.042)
LagoffupexcCN	-0.756***	-0.596***	-0.499***	-0.757***
	(0.137)	(0.106)	(0.175)	(0.120)
LagindownexcCN	2.737***	0.470**	0.317	0.414
	(0.304)	(0.195)	(0.293)	(0.357)
LaginupexcCN	2.902**	5.112***	7.653***	5.306***
	(1.202)	(0.918)	(1.878)	(1.102)
Observations	15496	15496	15496	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 11: Effects of inter-industry offshoring and inshoring to China on TFP (High-Medium and Medium-Low Tech Industries)

	High-Medium Tech				Medium-Low Tech			
	FD	DFD	SGMM	One-Stage	FD	DFD	SGMM	One-Stage
LaglnTFP		0.907***	0.963***	0.926***		0.926***	0.989***	0.926***
		(0.016)	(0.033)	(0.017)		(0.018)	(0.008)	(0.021)
LagoffdownCN	-5.902***	-3.006***	0.467	-2.759	0.664	-0.429	0.070	-0.335
	(0.889)	(0.866)	(1.346)	(2.223)	(0.431)	(0.307)	(0.493)	(0.629)
LagoffupCN	62.144***	40.096***	-10.165	38.457*	-0.607	5.895***	8.021***	6.679***
	(10.267)	(10.609)	(19.213)	(23.061)	(1.260)	(1.281)	(1.481)	(1.673)
LagindownCN	352.948***	310.257***	221.706*	212.262	-91.867***	7.560	-36.453**	9.849
	(79.345)	(100.677)	(127.928)	(146.031)	(17.011)	(13.815)	(18.237)	(37.301)
LaginupCN	-77.335*	-89.565*	-251.163***	-53.993	127.296**	-88.185	108.604*	-24.724
	(41.545)	(53.181)	(76.601)	(103.230)	(50.868)	(55.289)	(63.330)	(99.011)
LagSHHBE	-0.008	0.002	0.002	0.002	-0.020***	-0.003*	-0.008	-0.001
	(0.012)	(0.003)	(0.008)	(0.006)	(0.007)	(0.001)	(0.005)	(0.002)
LagSUBBE	0.016	0.002	-0.019	0.002	0.007	-0.001	-0.005	-0.000
	(0.017)	(0.003)	(0.011)	(0.005)	(0.009)	(0.002)	(0.006)	(0.003)
LagMNC	0.004	0.004	0.013	0.006	0.002	0.000	0.004	-0.002
	(0.014)	(0.003)	(0.010)	(0.006)	(0.012)	(0.003)	(0.008)	(0.004)
LagoffdownexcCN	0.242***	0.126*	-0.005	0.165	-0.148**	-0.052	0.257***	-0.015
	(0.081)	(0.070)	(0.109)	(0.329)	(0.071)	(0.069)	(0.098)	(0.096)
LagoffupexcCN	-4.093***	-2.475***	0.150	-2.618	0.005	-0.886***	-0.796***	-0.949***
	(0.524)	(0.570)	(1.024)	(2.283)	(0.181)	(0.161)	(0.215)	(0.239)
LagindownexcCN	-25.016**	-32.549***	-48.251***	-19.941	3.623***	-0.183	0.241	-0.058
	(10.706)	(10.751)	(13.842)	(38.508)	(0.395)	(0.287)	(0.365)	(0.608)
LaginupexcCN	42.574***	44.497***	16.254	39.907***	7.868***	4.277***	-2.990	3.695
	(5.433)	(5.801)	(11.009)	(9.750)	(1.809)	(1.172)	(1.865)	(3.292)
Observations	4438	4438	4438	3650	11058	11058	11058	9081

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 12: Effects of inter-industry offshoring and inshoring to China on TFP (Capital and Labor Intensive Industries)

	Capital Intensive				Labor Intensive			
	FD	DFD	SGMM	One-Stage	FD	DFD	SGMM	One-Stage
LaglnTFP		0.934***	1.007***	0.949***		0.903***	0.927***	0.924***
		(0.011)	(0.006)	(0.017)		(0.028)	(0.021)	(0.017)
LagoffdownCN	-3.879**	-3.452***	0.409	-3.189	-0.595**	-0.435**	-0.186	-0.296
	(1.533)	(1.129)	(1.656)	(2.828)	(0.296)	(0.205)	(0.434)	(0.360)
LagoffupCN	2.220	-9.620***	-13.115***	-8.674**	1.637	4.583***	8.221***	6.723**
	(2.723)	(2.599)	(4.327)	(3.637)	(1.430)	(1.530)	(2.121)	(2.613)
LagindownCN	667.040***	253.986	352.411	206.274	-156.714***	-26.134	9.412	-9.805
	(163.465)	(164.201)	(251.696)	(565.230)	(17.279)	(17.649)	(22.037)	(26.827)
LaginupCN	-17.867	35.777	-14.465	31.073	-11.377	27.468	21.557	38.705
	(32.725)	(34.483)	(42.927)	(68.449)	(32.717)	(40.760)	(52.994)	(51.459)
LagSHHBE	-0.013	-0.002	-0.006	-0.001	-0.022***	-0.001	0.001	0.000
	(0.009)	(0.002)	(0.006)	(0.003)	(0.008)	(0.002)	(0.006)	(0.002)
LagSUBBE	-0.001	0.001	-0.007	0.003	0.025***	-0.001	-0.002	-0.002
	(0.012)	(0.002)	(0.008)	(0.003)	(0.010)	(0.002)	(0.011)	(0.004)
LagMNC	-0.002	0.002	0.009	-0.000	0.008	0.001	0.003	0.002
	(0.014)	(0.003)	(0.007)	(0.004)	(0.011)	(0.003)	(0.011)	(0.004)
LagoffdownexcCN	0.176	0.350**	-0.030	0.315	0.138**	0.138***	0.234***	0.097**
	(0.159)	(0.153)	(0.133)	(0.316)	(0.067)	(0.045)	(0.084)	(0.046)
LagoffupexcCN	0.612**	0.376	0.582	0.451	-1.085***	-0.684***	-0.707**	-0.873***
	(0.288)	(0.237)	(0.420)	(0.382)	(0.182)	(0.182)	(0.280)	(0.332)
LagindownexcCN	-6.906*	-8.209**	-11.878*	-5.613	1.661***	0.670***	0.181	0.575*
	(3.611)	(4.045)	(6.459)	(13.893)	(0.275)	(0.241)	(0.344)	(0.322)
LaginupexcCN	10.405***	4.848***	5.752**	3.208	-17.365***	4.033**	5.965	5.987**
	(1.697)	(1.734)	(2.438)	(4.939)	(2.183)	(1.743)	(3.894)	(2.548)
Observations	7950	7950	7950	6534	7546	7546	7546	6197

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 13: Effects of inter-industry offshoring and inshoring to China on TFP (Relatively Upstream and Downstream Industries)

	Relative Upstream				Relative Downstream			
	FD	DFD	SGMM	One-Stage	FD	DFD	SGMM	One-Stage
LaglnTFP		0.912***	0.995***	0.920***		0.928***	0.957***	0.937***
		(0.036)	(0.010)	(0.017)		(0.020)	(0.013)	(0.013)
LagoffdownCN	12.612***	-1.418	-2.358	-1.434	-0.753	-0.888**	0.474	-0.478
	(1.422)	(1.424)	(1.885)	(2.162)	(0.516)	(0.429)	(0.658)	(2.384)
LagoffupCN	-22.902***	10.468**	23.346***	9.402	7.978***	14.973***	9.312**	13.062
	(4.427)	(4.153)	(6.192)	(7.374)	(2.535)	(2.557)	(4.450)	(14.408)
LagindownCN	-212.350***	54.233***	88.826***	56.530	-62.726	183.925**	78.505	101.304
	(25.848)	(20.456)	(28.730)	(42.404)	(72.248)	(82.572)	(105.740)	(274.711)
LaginupCN	-197.866***	-130.946***	-134.782**	-94.893	92.048***	46.135*	14.106	50.557
	(38.982)	(38.910)	(53.846)	(73.540)	(20.874)	(25.945)	(30.629)	(65.687)
LagSHHBE	-0.017**	-0.001	-0.007	0.000	-0.018*	-0.002	0.004	-0.002
	(0.008)	(0.002)	(0.006)	(0.002)	(0.009)	(0.002)	(0.007)	(0.003)
LagSUBBE	0.020**	0.001	-0.004	0.001	-0.005	-0.001	-0.004	-0.002
	(0.008)	(0.002)	(0.009)	(0.003)	(0.014)	(0.002)	(0.008)	(0.007)
LagMNC	0.009	0.001	-0.005	0.002	-0.003	0.002	0.013	0.002
	(0.013)	(0.003)	(0.007)	(0.005)	(0.013)	(0.003)	(0.010)	(0.006)
LagoffdownexcCN	-0.022	0.020	0.024	0.054	-0.079	0.021	-0.204	-0.005
	(0.095)	(0.104)	(0.134)	(0.189)	(0.098)	(0.076)	(0.137)	(0.352)
LagoffupexcCN	-0.982***	-0.853***	-0.709***	-0.955***	-1.270***	-1.480***	-0.566	-1.269
	(0.176)	(0.130)	(0.192)	(0.168)	(0.311)	(0.265)	(0.529)	(1.766)
LagindownexcCN	2.599***	-0.457	-0.733**	-0.405	3.034	-60.526***	-33.003	-46.106
	(0.359)	(0.299)	(0.373)	(0.596)	(16.866)	(18.807)	(27.078)	(71.588)
LaginupexcCN	-3.373**	2.458	2.297	2.850	18.491***	33.997***	34.789***	30.246***
	(1.647)	(1.691)	(2.139)	(1.968)	(3.264)	(4.068)	(4.764)	(7.727)
Observations	8631	8631	8631	7085	6865	6865	6865	5646

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 14: Effects of inter-industry offshoring and inshoring on TFP

	FD	DFD	SGMM	One-StageFE
LaglnTFP		0.938***	0.942***	0.946***
		(0.006)	(0.066)	(0.012)
Lagoffdown	-0.027	0.185***	0.252***	0.009
	(0.027)	(0.025)	(0.043)	(0.033)
Lagoffup	-0.838***	-0.917***	-1.073***	-0.097
	(0.268)	(0.181)	(0.364)	(0.202)
Lagindown	3.281***	0.761*	0.642	-0.262
	(0.995)	(0.442)	(0.717)	(0.450)
Laginup	-9.344***	15.028***	19.092***	2.602
	(3.387)	(2.413)	(5.449)	(2.605)
LagSHHBE	-0.065***	-0.002	-0.021	-0.007
	(0.014)	(0.003)	(0.014)	(0.007)
LagSUBBE	0.034*	0.001	-0.014	-0.004
	(0.018)	(0.003)	(0.014)	(0.011)
LagMNC	0.105***	0.016***	0.024	0.010
	(0.025)	(0.005)	(0.023)	(0.006)
Observations	15496	15496	15496	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the ACF two-step value-added with translog production function estimation procedure and are reported in parenthesis below point estimates.

Table 15: Effects of inter-industry offshoring and inshoring to China on TFP

	FD	DFD	SGMM	One-Stage
LaglnTFP		0.935***	0.899***	0.946***
		(0.006)	(0.075)	(0.013)
LagoffdownCN	0.814	-0.456	-0.470	-0.124
	(0.728)	(0.383)	(0.819)	(0.597)
LagoffupCN	8.439***	14.293***	20.444***	1.690
	(2.895)	(2.723)	(4.420)	(2.763)
LagindownCN	-654.059***	-285.791***	-2.770	-5.638
	(48.967)	(42.341)	(71.749)	(47.337)
LaginupCN	197.545***	198.529***	133.291	1.795
	(51.746)	(66.368)	(83.925)	(65.196)
LagSHHBE	-0.065***	-0.002	-0.012	-0.007
	(0.014)	(0.003)	(0.014)	(0.006)
LagSUBBE	0.033*	0.001	-0.015	-0.004
	(0.018)	(0.003)	(0.013)	(0.012)
LagMNC	0.106***	0.017***	0.022	0.010
	(0.025)	(0.005)	(0.022)	(0.007)
LagoffdownexcCN	-0.698***	0.079	-0.176	-0.047
	(0.146)	(0.102)	(0.202)	(0.116)
LagoffupexcCN	-1.253***	-1.592***	-1.872***	-0.217
	(0.378)	(0.274)	(0.565)	(0.271)
LagindownexcCN	10.613***	3.743***	0.398	-0.279
	(1.078)	(0.684)	(1.143)	(0.672)
LaginupexcCN	0.404	13.865***	20.487***	3.525
	(3.355)	(2.619)	(6.509)	(3.121)
Observations	15496	15496	15496	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the ACF two-step value-added with translog production function estimation procedure and are reported in parenthesis below point estimates.

Table 16: Robustness-Production Functions

	2ND	3RD	TR	CD
LaglnTFP	0.933***	0.937***	0.947***	0.964***
	(0.012)	(0.013)	(0.009)	(0.007)
Lagoffdown	0.067***	0.065**	0.070**	0.077**
	(0.012)	(0.033)	(0.035)	(0.030)
Lagoffup	-0.474***	-0.424***	-0.533**	-0.707***
	(0.067)	(0.056)	(0.208)	(0.241)
Lagindown	0.561***	0.498	0.294	0.062
	(0.180)	(1.138)	(0.607)	(0.560)
Laginup	6.161***	6.368	6.899***	9.142***
	(1.012)	(6.549)	(2.410)	(2.943)
LaglnTFP	0.933***	0.936***	0.947***	0.964***
	(0.014)	(0.014)	(0.011)	(0.006)
LagoffdownCN	-0.508	-0.348	-0.234	-0.323
	(0.325)	(2.023)	(0.629)	(0.691)
LagoffupCN	4.121***	5.203	4.686	7.067***
	(0.998)	(5.426)	(4.232)	(2.676)
LagindownCN	-2.581	-25.216	-32.246	-73.411
	(22.946)	(137.743)	(64.370)	(60.145)
LaginupCN	13.376	20.097	17.623	21.114
	(37.138)	(394.754)	(89.256)	(83.593)
Observations	12731	12731	12731	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 17: Robustness-Proxies, fix theta

	fix2000	fix2001	fix2002	varying
LaglnTFP	0.933***	0.934***	0.933***	0.933***
	(0.012)	(0.013)	(0.012)	(0.013)
Lagoffdown	0.067***	0.067***	0.066***	0.057***
	(0.012)	(0.008)	(0.010)	(0.009)
Lagoffup	-0.474***	-0.477***	-0.450***	-0.189*
	(0.067)	(0.081)	(0.064)	(0.100)
Lagindown	0.561***	0.616***	0.553***	0.486***
	(0.180)	(0.188)	(0.174)	(0.174)
Laginup	6.161***	5.668***	5.586***	1.540***
	(1.012)	(0.787)	(0.649)	(0.518)
LaglnTFP	0.933***	0.933***	0.933***	0.933***
	(0.014)	(0.011)	(0.013)	(0.013)
LagoffdownCN	-0.508	-0.512*	-0.520**	-0.346*
	(0.325)	(0.294)	(0.259)	(0.181)
LagoffupCN	4.121***	4.128***	3.890***	4.504***
	(0.998)	(0.931)	(0.988)	(1.311)
LagindownCN	-2.581	1.205	10.137	2.158
	(22.946)	(19.281)	(19.297)	(18.729)
LaginupCN	13.376	19.436	15.395	11.671
	(37.138)	(24.171)	(33.237)	(24.536)
Observations	12731	12731	12731	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 18: Robustness-Intra-industry proxies included

	No intra-industry	With intra-industry
LaglnTFP	0.933***	0.934***
	(0.012)	(0.011)
Lagoffdown	0.067***	0.060***
	(0.012)	(0.012)
Lagoffup	-0.474***	-0.375***
	(0.067)	(0.084)
Lagindown	0.561***	0.575***
	(0.180)	(0.193)
Laginup	6.161***	4.805***
	(1.012)	(1.028)
Lagoff		0.018
		(0.056)
Lagin		0.055
		(0.038)
LaglnTFP	0.933***	0.933***
	(0.014)	(0.011)
LagoffdownCN	-0.508	-0.526**
	(0.325)	(0.247)
LagoffupCN	4.121***	3.410**
	(0.998)	(1.361)
LagindownCN	-2.581	-3.557
	(22.946)	(24.310)
LaginupCN	13.376	26.928
	(37.138)	(28.229)
Lagoff		0.053
		(0.049)
Lagin		-0.073
		(0.077)
Observations	12731	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 19: Robustness-Trimming sample

	10%	5%	15%	20%	No trimming
LaglnTFP	0.933***	0.939***	0.931***	0.838***	0.981***
	(0.012)	(0.025)	(0.007)	(0.013)	(0.032)
Lagoffdown	0.067***	0.066***	0.066***	0.057**	0.044*
	(0.012)	(0.023)	(0.008)	(0.023)	(0.025)
Lagoffup	-0.474***	-0.455***	-0.478***	-0.416***	-0.869***
	(0.067)	(0.099)	(0.059)	(0.077)	(0.196)
Lagindown	0.561***	0.594*	0.585***	0.620**	-0.711
	(0.180)	(0.312)	(0.122)	(0.312)	(1.187)
Laginup	6.161***	4.885***	6.587***	6.727***	6.522**
	(1.012)	(1.149)	(0.863)	(0.707)	(2.861)
LaglnTFP	0.933***	0.938***	0.930***	0.838***	0.981***
	(0.014)	(0.026)	(0.007)	(0.013)	(0.031)
LagoffdownCN	-0.508	-0.379	-0.487**	-0.203	-1.183**
	(0.325)	(0.378)	(0.190)	(0.372)	(0.570)
LagoffupCN	4.121***	4.414**	4.222***	3.895***	-1.816
	(0.998)	(2.071)	(0.803)	(0.860)	(2.680)
LagindownCN	-2.581	-4.226	-5.695	-9.906	7.613
	(22.946)	(25.998)	(15.969)	(40.184)	(53.648)
LaginupCN	13.376	13.319	10.093	-21.113	48.287
	(37.138)	(45.565)	(21.248)	(20.374)	(81.911)
Observations	12731	12848	12601	12437	12948

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 20: Robustness-Timming assumption for labor

	Adj. lag	Adj. costs
LaglnTFP	0.933***	0.933***
	(0.012)	(0.010)
Lagoffdown	0.067***	0.067***
	(0.012)	(0.008)
Lagoffup	-0.474***	-0.474***
	(0.067)	(0.062)
Lagindown	0.561***	0.561***
	(0.180)	(0.182)
Laginup	6.161***	6.161***
	(1.012)	(0.737)
LaglnTFP	0.933***	0.933***
	(0.014)	(0.009)
LagoffdownCN	-0.508	-0.508**
	(0.325)	(0.204)
LagoffupCN	4.121***	4.120***
	(0.998)	(0.793)
LagindownCN	-2.581	-2.596
	(22.946)	(19.471)
LaginupCN	13.376	13.374
	(37.138)	(23.949)
Observations	12731	12731

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.

Table 21: Robustness-Firm FE

	No Firm FE	ll1	dl1	ll2	dl2
LaglnTFP	0.933***	-0.039	-0.031	-0.036	-0.008
	(0.012)	(0.076)	(0.053)	(0.081)	(0.049)
Lagoffdown	0.067***	0.053*	0.053**	0.053*	0.053***
	(0.012)	(0.027)	(0.025)	(0.028)	(0.016)
Lagoffup	-0.474***	-0.510**	-0.525***	-0.514***	-0.517***
	(0.067)	(0.204)	(0.107)	(0.186)	(0.102)
Lagindown	0.561***	1.169***	1.155**	1.164*	1.300***
	(0.180)	(0.433)	(0.506)	(0.645)	(0.376)
Laginup	6.161***	3.735	3.673	3.717	4.063*
	(1.012)	(3.642)	(2.634)	(3.506)	(2.126)
LaglnTFP	0.933***	-0.041	0.041	-0.039	0.042
	(0.014)	(0.073)	(0.062)	(0.065)	(0.047)
LagoffdownCN	-0.508	-0.090	-3.162***	-0.070	-2.941***
	(0.325)	(0.956)	(0.991)	(0.920)	(0.512)
LagoffupCN	4.121***	4.406*	10.661***	4.392	9.273***
	(0.998)	(2.269)	(2.610)	(2.876)	(1.624)
LagindownCN	-2.581	-57.529*	24.191	-57.823	0.495
	(22.946)	(29.933)	(43.352)	(39.869)	(20.479)
LaginupCN	13.376	56.340	1.946	56.335	5.707
	(37.138)	(53.852)	(43.764)	(50.115)	(27.963)
Observations	12731	9966	9966	9966	9780

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and are reported in parenthesis below point estimates.