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

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Abstract

In this paper we confirm the existence of improvements on firm productivity when domestic upstream and downstream firms 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 reduced trade barriers to China, help us confirm that these inter-industry productivity improvements can also be generated from a quasi-trade liberalisation event. Upstream linkages are the dominant source of these productivity benefits and are reaped mainly from medium-low tech, labor intensive and upstream industries. Finally, we draw upon the importance of biases in our results from misspecifications common in the literature. From ignoring the dynamic nature of productivity, results appear overestimated or with sign reversals. From estimating a value-added instead of a gross-output production function, results become spurious.

Keywords: Offshoring, supply chain, spillovers, productivity
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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/communication costs over the years, resulted in increasingly geographically fragmented value chains. This in turn, greatly impacted firm performance. Strand of the literature has examined the productivity effects from *intra-industry* offshoring, i.e changes in the offshoring intensity of firms within the industry.[2] However, it has neglected potential productivity effects from *inter-industry* offshoring. The latter refers to the offshoring activity undertaken by the domestic suppliers (upstream) or clients (downstream) of the focal firm.

In addition, we notice that the literature is silent about inshoring. Mirroring offshoring activity, it is defined as the export of final output that will be used as intermediate input to both affiliated and unaffiliated foreign firms.[3] Similarly, potential productivity effects from inter-industry inshoring are neglected. This refers to the inshoring activity undertaken by the domestic suppliers (upstream) or clients (downstream) 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 productivity gains. Such channels have never been examined under a unified framework and could be a source of major technology transfers. Second, we ask whether "opening up" to trade will impact firms' productivity via the prementioned inter-industry channels. We expect to provide policy-makers and institutions with evidence on the importance of trade liberalization episodes on firms' productivity, but now focusing on the inter-industry linkages. Finally, as a natural extension to the estimation procedure followed, we draw upon the importance of misspecifications common in the literature. This will allow us to identify the extent to which biases distort our results.

Using firm level data for Belgian manufacturing firms during 2002-2007, we estimate firm-level productivity. For this we follow the flexible two-step procedure of Gandhi et al. (2012) (henceforth GNR). This procedure allows us to control for severe value-added bias by estimating a gross-output production function. Using Input-Output tables we construct industry-level measures to proxy inter-industry offshoring and inshoring intensities based on a measure proposed by Merlevede and Michel (2013). Given the dynamic nature of productivity, we model any productivity effect as a learning process. Therefore, we allow inter-industry offshoring and inshoring to affect the future path of productivity.[4]

Firstly, we find strong evidence over the existence of inter-industry offshoring and inshoring effects on the productivity of 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 productivity improvement from inter-industry linkages corresponds to approximately two times the average productivity increase of Belgian manufacturing firms during 2002-2007. This predominantly originates from upstream linkages, while medium-low tech

[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); Tomiura (2007); Görg et al. (2008); Halpern et al. (2009); Ito and Tanaka (2010); Michel and Rycx (2014).

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

[4]For a similar treatment see Aw et al. (2008); De Loecker (2013); Doraszelski and Jaumandreu (2013).

(relatively less R&D intensive), labor intensive or upstream industries are the main recipients of these effects.

Secondly, 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 episode. This amounts to a 0.5% increase in the average productivity of Belgian firms and corresponds to 30% of the total increase in the average productivity of Belgian manufacturing firms during the period 2002-2007. Again, medium-low tech and labor intensive industries are the main beneficiaries, with all the productivity increase induced from upstream offshoring to China.

Lastly, we confirm the importance of biases in our results from misspecifications common in the literature. On the one hand, from ignoring the dynamic nature of productivity, results appear overestimated or with sign reversals. On the other hand, from estimating a value-added instead of a gross-output production function, results become spurious.

The rest of the paper is organised as follows: in Section 2, we provide an overview of the existing literature over the relationship between productivity, supply chains and offshoring-inshoring activity; in Section 3, we describe the data; in Section 4 we define how the relevant proxies are constructed and analyse their trends; in Section 5, we describe the empirical methodology followed; in Section 6 we present the main results for each of the three questions considered; in Section 7 we include a battery of robustness checks. Finally, Section 8 offers some concluding remarks.

2 Related Literature

A big strand of the literature is devoted to 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 (Markusen, 1989; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Connolly, 2003; Dragusanu, 2014; Antras et al., 2014). Empirical research at the firm and industry-level has confirmed strong productivity increases caused by importing intermediate inputs (Kasahara and Lapham, 2013; Halpern et al., 2009; Feenstra et al., 1992; Kasahara and Lapham, 2008; Muendler, 2004; Bernard et al., 2009, 2007). Closely related to this literature, studies using the alternative definition for imported intermediate inputs, offshoring or international outsourcing, have reported similar outcomes (Egger and Egger, 2006; Amiti and Wei, 2009; Görg et al., 2008; Tomiura, 2007; Kurz, 2006).

This strand of international trade 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) derived the productivity premium of exporting firms, while extensive empirical research confirmed such predictions.[5] In all these models exporting is considered as the action of selling final output to consumers abroad. To our knowledge though, no attention has been paid to the effect on firm's productivity from inshoring, i.e exporting final output for intermediate input usage by foreign firms.

These studies, have focused on the intra-industry (firm) effects from importing intermediate inputs or exporting while neglecting any inter-industry linkages. But firms operate in a complex environment where they are supplied from domestic upstream and supply domestic downstream

[5]See the following non-exhaustive sources: Melitz and Redding (2012); Redding (2010); Bernard et al. (2011); De Loecker (2007); Lileeva and Trefler (2010); Bustos (2011).

industries. If these domestic upstream and downstream industries become more productive from importing or exporting intermediate inputs as described above, we would expect such productivity improvements 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).[6]

This paper adds in the trade literature by filling the following gaps. We identify the effects on productivity from intermediate-input-driven technology transfers via inter-industry linkages, in a holistic framework. Also, we highlight the importance of trade openness on firm performance via inter-industry linkages. Finally, we emphasize the significance of value-added bias in production function estimations and specification 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. 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 a consistent 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 and ownership. For further details on 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.[7] Table 1, provides an overview of the NACE rev.1.1 2-digit industries included . 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 BACON method proposed by Billor et al. (2000).[8] Firms that re-enter or appear for only 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 due to insufficient number of observations for estimating a production function at the industry level. This results in an unbalanced panel of 2765 firms and 15496 observations for the period 2002-2007 (see Table 2).

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

[7] This refers to accounts not integrating the statements of the possible controlled subsidiaries or branches of the concerned company.

[8] BACON stands for block adaptive computationally efficient outlier nominators. It is a multiple outlier detection method. The variables we consider in the method are log values of output, labor, capital and material input. From the original non-trimmed sample, 1.8% is dropped.

All monetary variables are deflated using the appropriate NACE 2-digit deflator from EU KLEMS database. Real output *(Y)*, is 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 the number of employees. Firm wage *(W)*, is measured as the share of cost of employees over the number of employees.[9] Multinational status (MNC), is a dummy variable indicating a firm that at least 10% of its shares are owned by a singe foreign firm.

For the measurement of proxies we use the World Input-Output Database (WIOD). It is a time-series of Input-Output (IO) tables for forty countries worldwide and a case covering the rest of the world (RoW), for the period 1995-2011.[10] It also contains information on international supply and use tables (Int. SUTs) in current prices, expressed in millions of dollars. The latter allows us to split the proxies according to the country of origin of the trading partner, i.e China. Note that the WIOD industry classification (CPA) contains 35 industries and 59 products and is more aggregate than the Eurostat IO tables.[11]

The major advantage over other databases is that WIOD 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. Most importantly, within each end-use category they also differ by country of origin.[12] This provides greater variability over time and across different types of intermediate inputs and countries of origin. This extra level of detail is expected to unmask possible heterogeneity issues and provide better identification.

4 Inter-industry Offshoring and Inshoring

4.1 Definition and Measurement

For the measurement of inter-industry offshoring and inshoring activity, relevant proxies are 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. Respectively, ζ_{jut} is the proportion of industry j's intermediate inputs supplied from upstream industries u at time t. To eliminate distortion of relative magnitudes across time and industries and bring exact identification of inter-industry effects we fix the weights to year 2000 values. It also 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.

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

[10] 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.

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

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

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 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 at the same time are offshored by the latter two. This refinement departs from simple industry averages common in the literature. It allows 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 domestic firm has 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 Grossman and Helpman (1994); Coe and Helpman (1995); Connolly (2003)).

Overall, they are inherently relative measures interpreted as: firms with larger values for $Down\_off_{jt}$ (Up_off_{jt}) are those that face relatively more downstream (upstream) offshoring. For each proxy we identify the total impact from all the possible mechanisms in motion. Note that the possible mechanisms for each case could me more than one: knowledge and R&D spillovers, management practices, international networking, organisational restructuring, reduction of X-inefficiencies, import competition and quality standards.

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 respectively. 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 generating technology transfers 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 yearly averages for all manufacturing industries of inter-industry offshoring and inshoring intensities.

The left figure shows downstream offshroring fluctuating vastly over time leading to an average increase during 2002-2007. This can be reconciled 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 demand for intermediate inputs. , firms adjust fast to a wider set of offshoring opportunities. On the other hand, the dashed line on the same figure reveals a stable decrease over time for upstream offshoring. This is consistent with industries that are upstream in the value chain 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 only final products that are exported for intermediate input use by other firms and not final consumption by consumers. This trend is in line with Belgium being a small and heavily trade oriented economy. Exports of goods and services has been growing since 1995 representing 77.5% of the country's GDP in 2007 (OECD, 2015a).

Figure 2, depicts the evolution of our proxies focusing on a specific trading partner i.e China. 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 trade liberalization episode with a specific country.

It is clear 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 productivity via inter-industry linkages.

5 Empirical Methodology

5.1 Productivity

We consider a flexible gross output production function $Y_{it} = F_t(K_{it}, L_{it}, M_{it})e^{\omega_{it}+\epsilon_{it}}$, with Hicks-neutral productivity ω_{it} (henceforth TFP). In logs, the production function to be estimated 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 econometricians but known to the firm. Shocks ex-post to firm's decisions and production are picked up by ϵ_{it}.[13]

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 (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006; Wooldridge, 2009)(henceforth OP, LP, ACF and Wooldridge respectively). The main focus is to solve for endogeneity, otherwise known as "simultaneity" or "transmission bias". This originates from the fact that firms choose inputs while knowing their productivity level (Marschak and Andrews, 1944; Griliches and Mairesse, 1999).

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 Mendershausen (1938); Marschak and Andrews (1944); Bond and Söderbom (2005); Ackerberg et al. (2006) and formalised by GNR. Intuitively, there is not enough variation outside the production function system to identify the flexible variable input.[14]

To circumvent this problem, applied economists focus on value-added production functions i.e subtract materials from output. But this specification fails to identify the true variable of interest i.e TFP, even under very strong assumptions (Bruno, 1978; Diewert, 1978). As a result, estimates suffer from "value-added bias", overstating the dispersion and heterogeneity in TFP across industries. Intuitively, this results from erroneously attributing the variation of material inputs in productivity while we should be controlling for it as an input in the production function. This is an at least equally important source of bias as the "transmission bias". Productivity margins of any variable of interest, (e.g exporting or importing activity) are significantly overestimated. Therefore we end up with a distorted image of the true productivity impact and consequently misleading policy implications (GNR). [15]

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 the firm's static profit maximization problem. This flexible approach controls for both transmission and value-added bias. It imposes

[13]Given that y_{it} is an observable variable in our dataset, we expect ϵ_{it} to also contain measurement error to output and prices. This is assumed to be symmetric across firms within each industry and therefore not affecting our estimation.

[14]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 (Griliches and Mairesse, 1999; Ackerberg et al., 2007) (henceforth GM and ABBP, respectively). Therefore, in most datasets prices will capture market power and input/output quality differences rendering them endogenous (Fox and Smeets, 2011; Kugler and Verhoogen, 2012; Atalay, 2014).

[15]For a detailed discussion on value-added bias and its implications see Section 6.3.

no specific functional form for the production function. In addition, it does not rely on strong assumptions imposed from alternative proxy variable frameworks. An example is the assumption of scalar unobservability or bijection, necessary to invert the proxy demand function (see OP, LP, ACF, ABBP,GNR). In line with most of the the proxy variable methods the procedure follows two steps. But also it exploits information within the model to secure identification for gross output production functions with at least one flexible input of production.

Overall, estimation of the production function is at the CPA industry level, based on the two step nonparametric estimator of GNR. Using estimates of the production function coefficients at the CPA industry level, we retrieve productivity estimates $\hat{\omega_{it}}$, for firm i at time t. 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). Practically, it also includes the impact of inputs that are not explicitly measured as such (e.g intangibles such as marketing, management and human capital skills among others). In addition, we 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 (Klette and Griliches, 1996; De Loecker, 2011).[16]

5.2 Effects of Inter-industry Offshoring and Inshoring on TFP

In this subsection, we specify how we model the effects of inter-industry offshoring and inshoring on productivity. Recall that we identify all productivity effects as a learning process. We start with frequently encountered in the literature two-stage specifications and argue why they are misspecified. Then we present the correctly specified one-stage procedure upon which inference will be drawn.

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.[17]

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 its dynamic nature. 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:

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

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.

[16]In the robustness section we provide results for the case of imperfect competition in the output market. More structure is imposed on the same estimation procedure and results remain robust.

[17]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 for any positive amount of ownership.

In the case of firm fixed effects the above specification is inconsistent. To solve for the endogeneity induced by the dynamic nature of productivity we apply "System GMM".[18],[19]

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 lagged proxies and other determinants that are in the firm's information set when decisions are made. On the other hand, under the exogenous Markov process assumption used in the first-stage, we do not take into account these inter-industry effects and other determinants that possibly shift the future productivity path.

To solve for this inconsistency, we 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 since stage two is irrelevant.[20] 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 in the economy respectively.[21]

For both one-stage and two-stage procedures there is no closed form solution for the standard errors. Also for the latter, the inclusion of estimated productivity in the second stage introduces measurement error that will deflate the standard errors. To accommodate both concerns, bootstrapping is applied in each estimation. 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.[22]

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. Firstly, in all proxies we fix the technical coefficients θ_{jdt} and ζ_{jdt} to values of year 2000. This way we eliminate from our proxies the endogenous choice of the focal firm over which downstream or upstream firms

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

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

[20] 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 since it ignores the dynamic nature of TFP and provides an equilibrium relationship between TFP and variables of interest, irrelevant to our research. In practice, it only helps to control for unobserved price changes induced from the relevant shocks.

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

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

to cooperate with. Also, 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. By construction it alleviates concerns for simultaneity bias since 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, given the way proxies are computed, it is possible to have intermediate-input 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 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 MNC 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, lagged values of the proxies are considered as exogenous and thus orthogonal to the error term.

6 Results

In this section we report the following: 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 bias for our results from misspecifications common in the literature. The variables included in every specification include all inter-industry offshoring and inshoring proxies: downstream offshoring; upstream offshoring; downstream inshoring; and upstream inshoring.

Separate regressions for each proxy would run the risk of omitted variable bias. This is because we would exclude both supply-demand linkages and their interactions that could have offsetting or multiplying effects for some mechanisms i.e x-inefficiencies reductions or innovation and knowledge spillovers respectively. 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.[23]

For each Table in this section we report the following: in the first column the static specification (3) (henceforth FE); in the second column the dynamic specification (4) (henceforth DFE); in the third column the dynamic specification (4) controlling for firm fixed effects (henceforth SGMM); and in the forth column the correctly specified One-stage procedure (henceforth One-stage).[24] All regressions 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 other 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 based on theoretical and empirical predictions where on average

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

[24]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.

multinationals appear to be more productive. This result is rationalised in section 6.3.

The reason we report static specification (3), eventhough misspecified, is its frequent use in the empirical trade literature. Going through the main results of the paper in Tables 6-13 we observe that the sign, scale and significance of the coefficients in the first column are not consistent with the rest of specifications, leading to distorted inference. Therefore, it is crucial to at least control for the dynamic nature of productivity. To draw the attention of researchers over its importance, we keep reporting it in the first column of each table produced in this section.

Specifications presented in column two (DFE) and three (SGMM) in each of the tables are misspecified, as argued in the previous section. Despite this, they are expected to provide reasonable estimates since they control for a big source of bias generated when ignoring the dynamic nature of productivity. Overall, our interpretations are based on the correctly specified One-stage approach reported on the last column of each table.

Based on Fally (2011), R&D intensive industries became relatively less fragmented over time. Therefore, less R&D 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.[25]

Further heterogeneity can be uncovered once we consider the work of Antràs (2003), where on a property-rights based model, the internationalisation decision of the firm depends 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.[26]

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 both selling domestically and exporting their output to consumers for final use more intensively. Overall, relatively less output is expected to end up for domestic exchange between firms in relatively downstream sectors and therefore relatively upstream industries are prone to absorb most of the productivity effects from inter-industry linkages.[27]

To account for this possible heterogeneity, we generate an industry-level measure of relative production-line position as in Fally (2011); Antràs et al. (2012) 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

[25] Definition of categories is based on R&D 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).

[26] 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).

[27] Theoretical predictions of Antràs and Chor (2013) show that the incentive to integrate suppliers varies systematically with the relative position at which the supplier enters the production line. The nature of 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 that relatively upstream or downstream firms vary on the way they absorb the inter-industry effects as they vary on their integration intensities.

the distribution of the upstreamness measure as in Table 5.[28] We observe that primary and resource-extracting industries tend to be relatively upstream as in Antràs et al. (2012).

6.1 TFP Effects from Inter-industry Offshoring and Inshoring

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

Both upstream and downstream inshoring intensive sectors generate a positive and significant effect on TFP of the focal firm. Based on how the proxies are computed, 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.[29] 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 latter 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 latter 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%.[30] 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

[28] 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).

[29] 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 qualitative the same and with marginally higher magnitudes.

[30] 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.

reconciled with the fact that R&D 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 taken 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).

6.2 TFP Effects from Inter-industry Offshoring to and Inshoring from China

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).[31] 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 or exporting 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 for 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 closer 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 to and downstream inshoring from China have in most of the cases opposite directions. This could be interpreted under the scope that different trading partner characteristics generate heterogeneous effects (Manova and Zhang, 2012; Helpman et al., 2007; Chaney, 2008).[32]

As reported from Table 11 all the productivity gains are reaped 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

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

[32] For the rest of the proxies where trade excCN is considered, results are similar both quantitatively and qualitatively.

statistically significant only at 10% and hence avoid to consider it as a strong economically significantly interpretable impact.

Continuing, based on Table 12 we see that upstream offshoring to China is making on average firms in labor intensive industries more productive by approximately 0.91% while 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 quasi-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.

6.3 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.[33] [34] 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 latter 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 5, 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 latter estimation procedure generates more heterogeneous and dispersed productivity estimates. In addition, from Figure 6 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.[35]

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

[33]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).

[34]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.

[35]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.

and 15 that are directly comparable with table 6 and 10.[36]

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 (GNR).

6.4 Thought Experiment

As proved from GNR, gross-output production functions with at least one flexible input are nonparametrically non identified under any of the traditional dynamic and semi-parametric estimation methods. Intuitively, there is not enough variation outside the production function system to identify the flexible input.

In this section, we proceed as if we are not aware of this result. Therefore, we erroneously estimate a gross-output production function using the ACF estimation procedure.[37] The estimation is computationally feasible but does not identify the true production function. Therefore, estimates of ω_{it} do not represent TFP. A natural question that arises is how far these estimates are from the correctly identified ones in the GNR procedure.

We start with a visual inspection of the estimated elasticities of substitution for each input. On the one hand, the last set of results in Table 4, suggests that both the average elasticities of capital $\hat{\theta_k}$, labor $\hat{\theta_l}$, materials $\hat{\theta_m}$ and the average returns to scale (RTS) are within the expected range suggested by production function theory. On the other hand, compared to the identifiable GNR procedure, $\hat{\theta_l}$, $\hat{\theta_m}$ and RTS are overestimated while $\hat{\theta_k}$ is underestimated. Consequently, this should generate differences also in the distribution of estimated TFP.

Surprisingly, as shown in Figure 7, the TFP distribution using gross-output ACF is closer to the one under the GNR procedure. Seemingly the value-added bias is controlled from the fact that we employ a gross-output specification. But from Figure 8, we observe that the productivity distribution of MNCs visually dominates that of the non-MNCs as in the case of ACF with a value-added production function. Therefore, estimates are also expected to give misleading results.

To test the magnitude of the fallacy, we re-estimate specifications from the main body of the paper, based on the erroneous productivity estimates under ACF two-step procedure with a gross-output production function. Results are reported in table 16 and 17.[38] The correctly specified One-stage procedure fails to produce any significant results for the variables of interest. On the other hand, we see that learning from being a MNC increases productivity on average by 0.3% at 10% level of significance. This is a spurious result not existing under the identified estimation procedure of GNR.

From this simple exercise, we emphasize the importance of correctly identifying gross-output production functions. Numerical computation does not guarantee identification. Even in the case that we know prices, we can numerically estimate a production function where the estimates

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

[37]The procedure is similar to the one in Appendix C but with a gross-output translog production function.

[38]For the cases that the sample is split to extract heterogeneity, results are not reported but follow the same pattern and are available upon request.

deceivingly appear as “appropriate”. But this does not imply that we will be identifying the true production function. Prices are most likely endogenous and therefore cannot help in identification.

Overall, researchers should keep in mind that this identification issue distorts empirical results and in turn shifts theory to research questions irrelevant to the state of the world.

7 Robustness

To easily compare results, in each table for any of the following cases, the first column includes the baseline estimation procedure as presented in the main body of the paper. In addition, the lower panel considers the case where we split the proxies to China and rest of the world.

In columns two and three of Table 18, we assume a parametric Translog and Cobb Douglas production function respectively. Qualitatively, results are in line with the flexible production function as in the first column. Quantitatively, note that by moving from a flexible to a restricted functional form, point estimates are overestimated. A sensible explanation can be the a priori restrictions imposed on the functional form i.e curvature of production function and the elasticity of substitution between inputs. Intuitively, we erroneously impose variation from the production function to the Hicks-neutral productivity term that will bias our results. This confirms the importance of allowing flexible functional forms as raised by Yatchew (1998); Hulten (2001, 2010).

Table 19, tests for possible omitted variable bias from excluding intra-industry decisions. Therefore, in column two, we add in our baseline specification intra-industry offshoring (A.1) and inshoring (A.9). Results are robust with minor discrepancies in some point estimates.[39] Furthermore, intra-industry offshoring and inshoring intensities do not appear to significantly impact the productivity of firms.

In the first three columns of Table 20, results are robust to fixing the technical coefficients of the proxies to values of year 2001 and 2002.[40] In the last column, we allow for these weights to vary. Results are qualitatively but not quantitatively the same. This supports the idea that by fixing these weights, we eliminate distortions of relative magnitudes across time and industries and bring exact identification for the variables of interest.

From the first four columns of Table 21 we observe that results are robust to various trimming levels using the Bacon method proposed by Billor et al. (2000). Last column, clearly suggests that results are driven by inhomogeneities in the data. Therefore, it is imperative to control for outliers with a relevant trimming method.

Results are not affected when considering an alternative assumption for adjustment frictions in labor. In column two of Table 22, labor is assumed to be a flexible input but subject to adjustment costs such as firing and hiring costs. This means that labor is chosen during the realisation of productivity ω_{it} i.e. between $t-1$ and t. Therefore, to guarantee identification in the second step of GNR procedure, we use l_{it-1} instead of l_{it} in the orthogonality conditions.

A benefit of the GNR identification procedure is that we can easily incorporate firm fixed effects in productivity. The first step is unaltered, while the second step is augmented by subtracting the equation to be identified with its $t-1$ counterpart. Therefore, we eliminate fixed effects à la Arellano and Bond (1991). In column two, the instruments used to identify the first differenced equation, are as in the baseline procedure but lagged one year. In column three they are lagged two years in order to account for first order autocorrelation in the productivity innovation. Results are qualitatively similar with higher standard errors making some channels statistically insignificant. Note that this procedure should be treated with a grain of salt since we loose almost 25% of total information.

[39] Multicollinearity induced from intra-industry and inter-industry proxies can be the source of such discrepancies. This argument, supports our initial unwillingness to introduce intra-industry proxies in the baseline specification.

[40] See Appendix A for a detailed description on the construction of proxies.

Finally, we account for the case of imperfect competition in the output market. To control for unobserved variation in firm-specific prices we introduce more structure and assumptions (e.g iso-elastic demand system) as in Gandhi et al. (2012). By accounting for imperfect competition in the output market (see column two of Table 24), the economically interpretable productivity gains from inter-industry offshoring and inshoring are in total reduced by 0.5 percentage points.[41]

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 not prevalent previously. 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.

[41] For similar approach and results see Klette and Griliches (1996); De Loecker (2011).

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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} refers to imported intermediate inputs and TII_{jt} for total non-energy intermediate inputs of industry j at time t.[42] Due to data limitations, our definition of offshoring also includes production transfers within multinationals (vertical FDI), where intermediate inputs flow between affiliated companies. Proxies are computed using symmetric IO tables 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 including RoW treated as the Rest of World.[43] Summing (A.2) across all countries we retrieve proxy (A.1).

These proxies are not of any direct interest to us, as extensive research is already conducted. They serve as an intermediate step over the natural evolution for the construction of the proxies of interest in the next sections.

A.1.1 Downstream Offshoring

The previous measure of offshoring, limits our attention on the effects of offshoring within the industry. For example, how firms in the Manufacture of Ruber and Plastics are affected from offshoring. Clearly, this measure ignores any inter-industry linkages. 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 upstream Manufacture of Ruber and Plastics.

To capture the effect transmitted to firms in the supplying industry from the offshoring activity undertaken by firms in downstream industries, we compute a proxy at the industry-level. This proxy was 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 from domestic downstream industries. This proxy provides a linkage through which any change

[42] 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 latter case.

[43] 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 and RoW.

in the offshoring intensity of downstream firms will impact domestic upstream 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 International Supply tables we 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 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 upstream industry j and also offshore to foreign countries. All 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, $P_{jd} = P_j^{SUP} \cap P_d^{USE}$. Given that WIOD tables contain 59 product categories and 35 industries, P_{jd} will in some combinations of jd contain more than one products. This extra level of detail, captures the importance of secondary output as well.[44]

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 used in industry d.

The extent to which imports of intermediate products n by downstream industry d affect focal industry j, is measured 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 are also offshored by the latter, P_{jd}:

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

where the weight $\delta_{jnt} = Y_{jnt} / \sum_{p^n \subset P_j^{SUP}} Y_{jnt}$, captures the relative importance of final product n for industry j. It is 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 downstream industries d that j 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 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 industries and bring exact identification of the downstream offshoring effects. In addition, we can more easily argue over the exogeneity of the proxy on the idiosyncratic error of the productivity estimates.

[44] There is no consensus in the literature over which sectors should be included in the measures. Our benchmark proxy contains 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 that result in similar patterns.

Overall, $Down\_off_{jt}^{fix\theta_{2000}}$ is our baseline proxy for downstream offshoring, where higher values are interpreted as industry j facing higher downstream offshoring.[45]

Using WIOD tables we further split the proxy 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, refers to any foreign country that firms in downstream industry d offshore product n to. Following the previous procedure we compute for each *origin*:

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

Summing (A.6) across all origin we retrieve (A.5).

A.1.2 Upstream Offshoring

Downstream offshoring represents the vertical supply linkages of inter-industry offshoring. Respectively, there are vertical demand linkages that could allow for these effects to be transmitted from the opposite direction. For example, suppose that a firm in focal industry j demands intermediate inputs from firms in upstream industry u. Shifts in the offshoring intensity of u could impact the performance of j.

This effect, is generated from the offshoring activity of upstream industry u and transferred via the production process of its final product(s) that are later on supplied as intermediate inputs to firms in industry j. For instance, if the 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 latter increasingly offshores to foreign countries, we would expect the Belgian Manufacture of Wearing Apparel and Furs to experience a productivity effect.

Possible mechanisms inducing these effects, 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. Each one of them can lead to opposite direction effects that we cannot separately identify with the data in hand. The proxy proposed below, captures the overall direction and magnitude of this effect, from any possible mechanism in motion.

We define the offshoring effects via vertical demand linkages as upstream offshoring. A proxy to quantify, 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 $\Psi_{jut} = \sum_{p^n \subset P_{ju}} \gamma_{jnt} off_{unt}$, measures the extent to which the offshoring activity of upstream industry u affects industry j.[46] The weight γ_{jnt}, is computed from International Use tables. It captures the relative importance of intermediate product n over all intermediate inputs used from industry j. The technical coefficient ζ_{jut}, is computed from the WIOT and measures the relative importance of upstream industry u over all domestic upstream industries u that j sources from.[47]

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

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

Summing (A.8) across all origin we retrieve (A.7).

[45] For brevity, we suppress the index θ_{2000} for the rest of the cases.

[46] 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 offshored by u but not used by downstream industry j.

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

A.2 Inshoring

For a holistic assessment of the inter-industry effects of internationalization it would be incorrect to restrict our attention only to offshoring. We should also examine the mirror action 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.[48]

We 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 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. WIOD provides time-series of world IO 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). 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 inshore from:

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

Summing (A.10) across all origin we retrieve (A.9).

A.2.1 Downstream Inshoring

To capture the effect from inter-industry inshoring, we introduce for the first time a proxy 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 latter starts to increasingly export its final product to other firms only for intermediate input usage i.e inshoring. This increase in the inshoring intensity of downstream Manufacture of Office Machinery and Computers is likely to affect the productivity of the supplying Manufacture of Computer and Related Services. The mechanisms generating these effects can vary from the need for increased quality of intermediate inputs in order to meet exporting standards to innovation or knowledge spillovers. As before, we capture the overall direction and magnitude of this effect from any possible mechanism in motion.

We define this inter-industry linkage as downstream inshoring:

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

where $\Lambda_{jdt} = \sum_{p^n \subset P_{jd}} \delta_{jdt} in_{dnt}$, measures the extent to which the inshoring activity of downstream industry d affects industry j.[49] As mentioned before, in_{dnt} proxies the inshoring intensity of industry d for product n. It is calculated using the International Use tables, i.e the share of product n exported by industry d and used as intermediate input. Weights δ_{jnt} and θ_{jdt} are as before.[50]

[48] 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.

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

[50] For identification reasons we fix θ_{jdt} to year 2000 as before.

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

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

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 $\Xi_{jut} = \sum_{p^n \subset P_{ju}} \gamma_{jnt} in_{unt}$, measures the extent to which the inshoring activity of domestic upstream industry u affects focal industry j. The weights γ_{jnt} and ζ_{jut} are computed as before.[51] Again, the mechanisms generating these effects can be various i.e organisational restructuring, international network sharing, quality standards and reverse engineering. As before, we capture the overall direction and magnitude of this effect from any possible mechanism in motion.

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

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

Summing (A.14) across all origin we retrieve (A.13).

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

B GNR Two-step Estimation Procedure

This section serves as an overview of the basic steps and assumptions in the GNR two-step estimation procedure. For a detailed and complete description of the estimation procedure refer to Gandhi et al. (2012).

This case considers the classic environment of perfect competition in both input and output markets. Capital is a quasi-fixed input and therefore chosen one year prior to the realisation of productivity $(t-1)$. Rigidities in Belgian labor market, induce high labor adjustment frictions. This is translated to an adjustment lag resulting in a one year time lag between the choice of labor and its realisation. Therefore, labor is a dynamic input chosen one year before the productivity realisation.[52] 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 and other firm characteristics, firm's static profit maximisation problem yields the first order condition with respect to the flexible input, material:

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

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, $\mathcal{E} = E(\mathrm{e}^{\epsilon_{it}})$.[53] 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}, 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 of order r. This step, non-parametrically identifies 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:

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

[52] For similar treatment see De Loecker et al. (2014); Konings and Vanormelingen (2015). In the robustness section, we consider alternative definitions of adjustment frictions such as adjustment costs (hiring/firing costs).

[53] We inherently assume that the existence of any measurement error is symmetric across firms and thus does not affect our results. We would like to thank David Rivers for pointing this out.

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 $\mathcal{B}_t(L_{it}, K_{it})$ is the constant of integration, 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 assumed, $\omega_{it} = g_{it}(\omega_{it-1}) + \xi_{it}$. However, exogeneity is relaxed in order to accommodate concerns raised by Aw et al. (2008); De Loecker (2013); De Loecker and Goldberg (2013); Doraszelski and Jaumandreu (2013). Lagged and observable variables $s_{it-1} = (MNC_{it-1}, SUB^{BE}_{it-1}, SHH^{BE}_{it-1}, proxies_{t-1})$ are allowed to affect current productivity outcomes, $\omega_{it} = g_{it}(\omega_{it-1}, s_{it-1}) + \xi_{it}$. We can now express the innovation of productivity ξ_{it} as a function of the parameters of the constant of integral to be estimated $\xi_{it}(\alpha)$, by 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:

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

where capital and labor are quasi-fixed inputs decided one year before and thus orthogonal to the innovation of productivity.[54]

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

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

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).

[54] Consistency and assymptotic normality of functionals of f (such as moments and productivity distribution) follow from Chen et al. (2014) and Chen and Pouzo (2015).

C ACF Two-step Estimation Procedure

This section serves as an overview of the basic steps and assumptions in the ACF two-step estimation procedure. For a detailed and complete description of the estimation procedure refer to Ackerberg et al. (2006). 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 employ a value-added production function with a log additive Hicks-neutral productivity term, $VA_{it} = Y_{it} - M_{it} = F(K_{it}, L_{it})e^{\omega_{it}}$. 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:

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

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

Conditional on the state variables and other firm characteristics, 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, proxies and wages.[55] To control for unobserved productivity ω_{it}, we use the inverted intermediate input demand $\omega_{it} = m^{-1}(l_{it}, k_{it}, m_{it}, z_{it})$. To approximate the latter, we use a third-order polynomial of l_{it}, k_{it}, m_{it}, while z_{it} is introduced additively in order to restrict the parameter space that we search over. Also, time and region dummies are included additively controlling for shocks varying across time and regions. [56]

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 in output, $\hat{\phi}_{it}$. Continuing, productivity can be expressed 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 $\omega_{it} = g_{it}(\omega_{it-1}, s_{it-1}) + \xi_{it}$. We can now express the innovation of 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 step two, the coefficients of the production function are estimated with a standard GMM procedure. The moments used are $E(\xi_{it} n_{it}) = 0$. Orthogonality conditions depend on the timing assumptions of inputs:

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

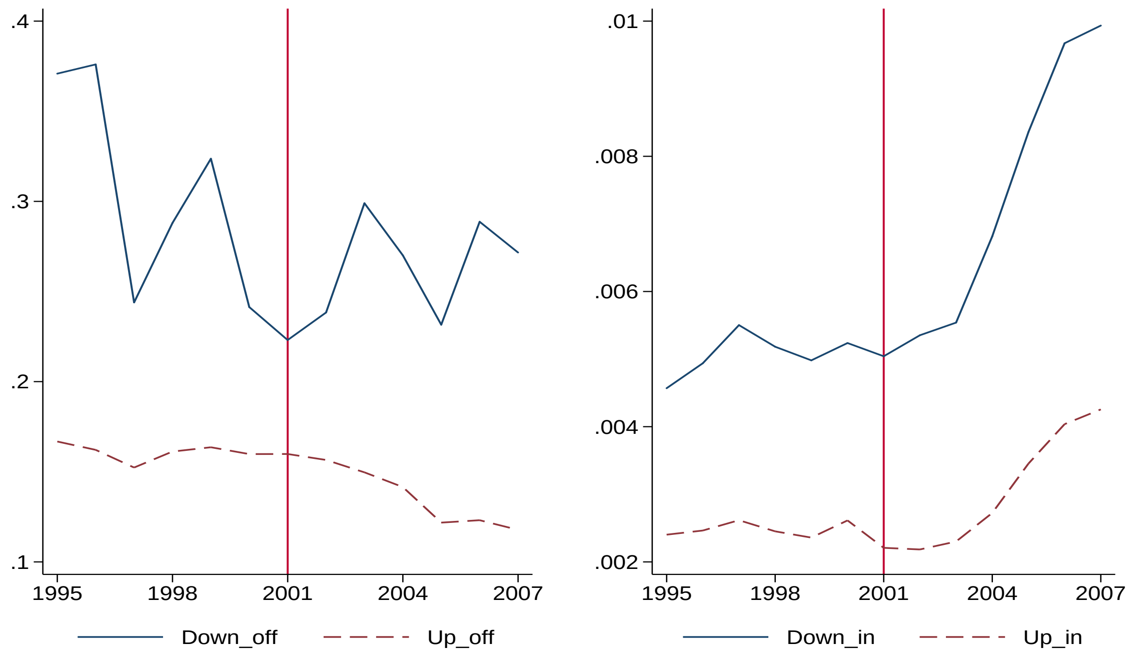
where capital and labor are quasi-fixed inputs decided one year before and thus orthogonal to the innovation of productivity. Using estimates of the production function coefficients $\hat{\gamma}$ at the CPA industry level, we retrieve productivity estimates $\hat{\omega_{it}}$ for firm i in industry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

[55] 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).

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

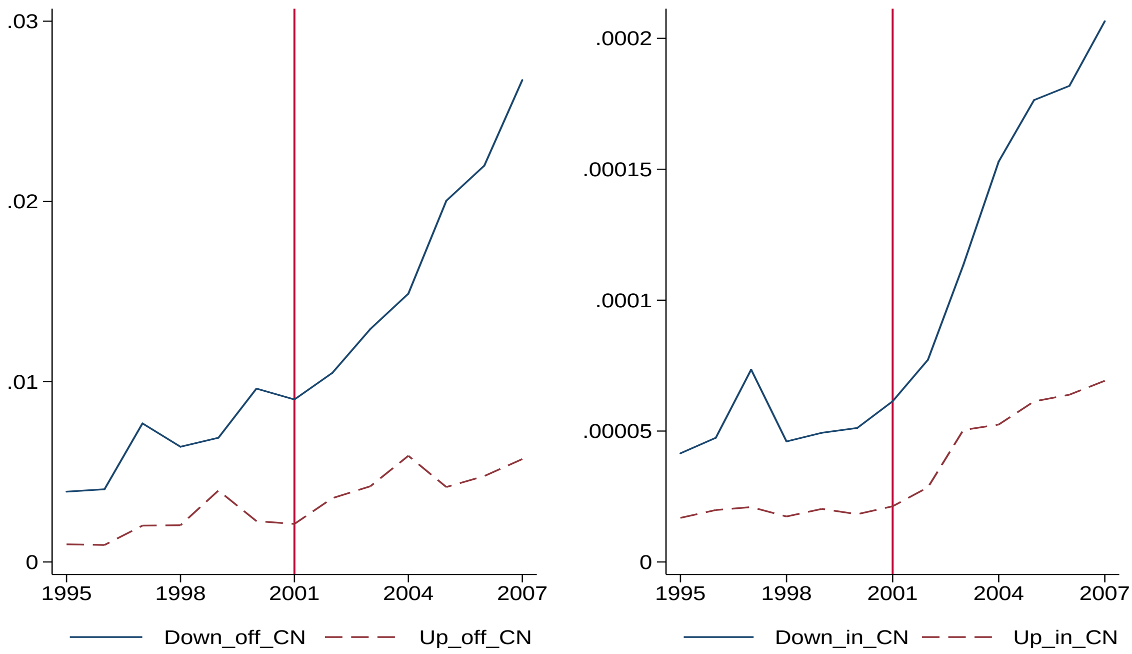
D Figures and Tables

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



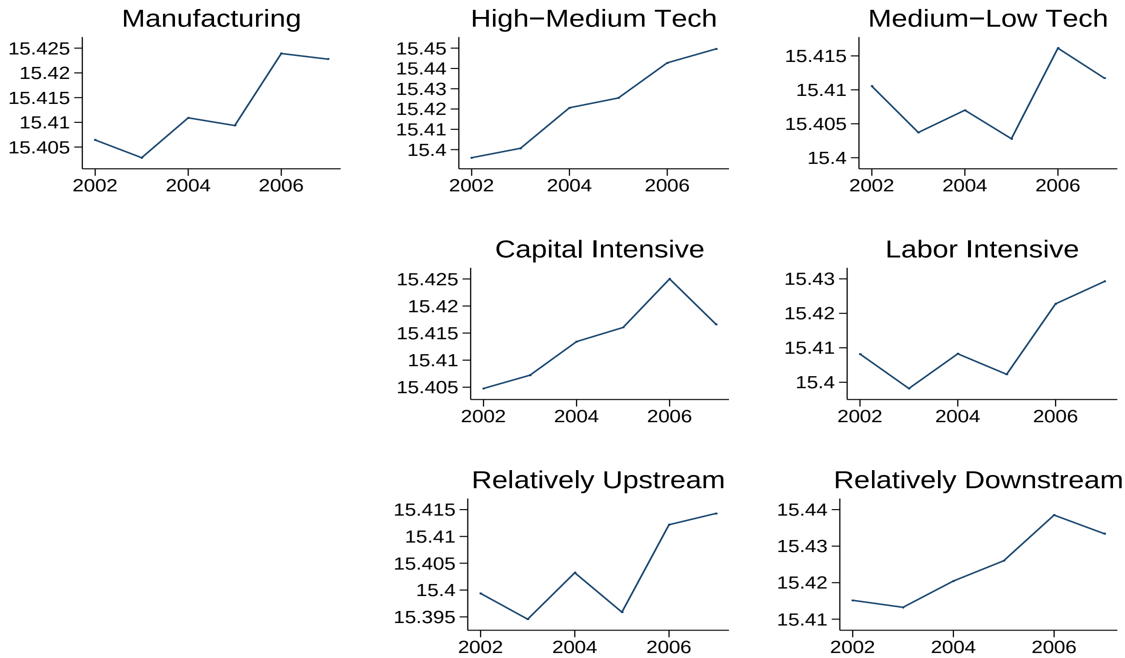
Source: Own calculations using World Input Output Database (WIOD)

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



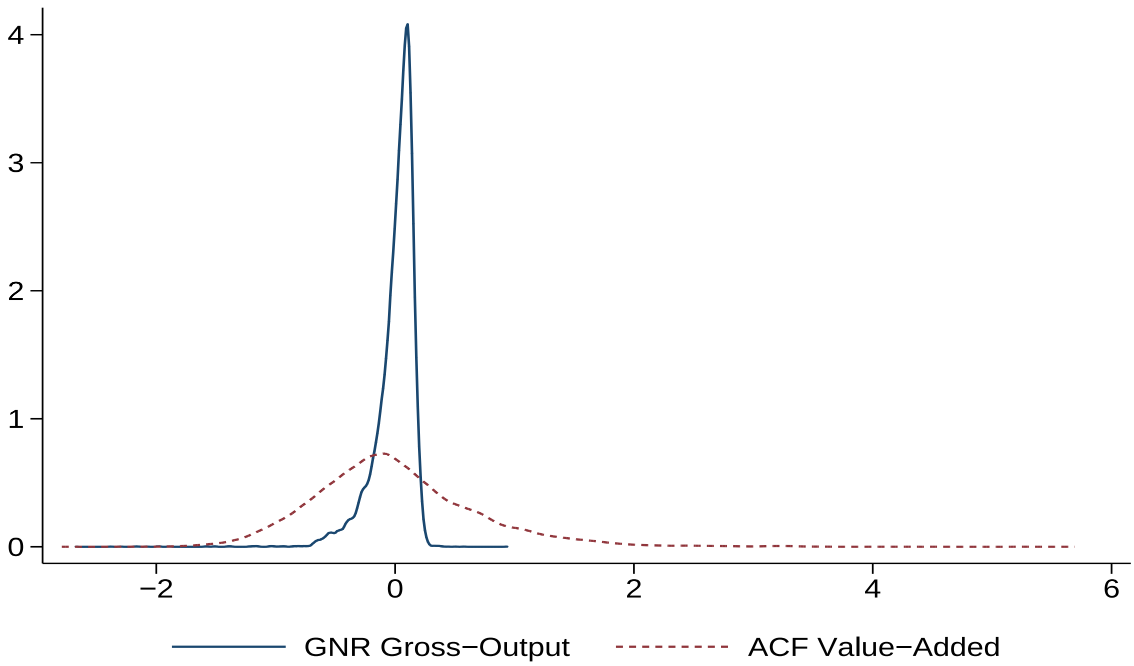
Source: Own calculations using World Input Output Database (WIOD)

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



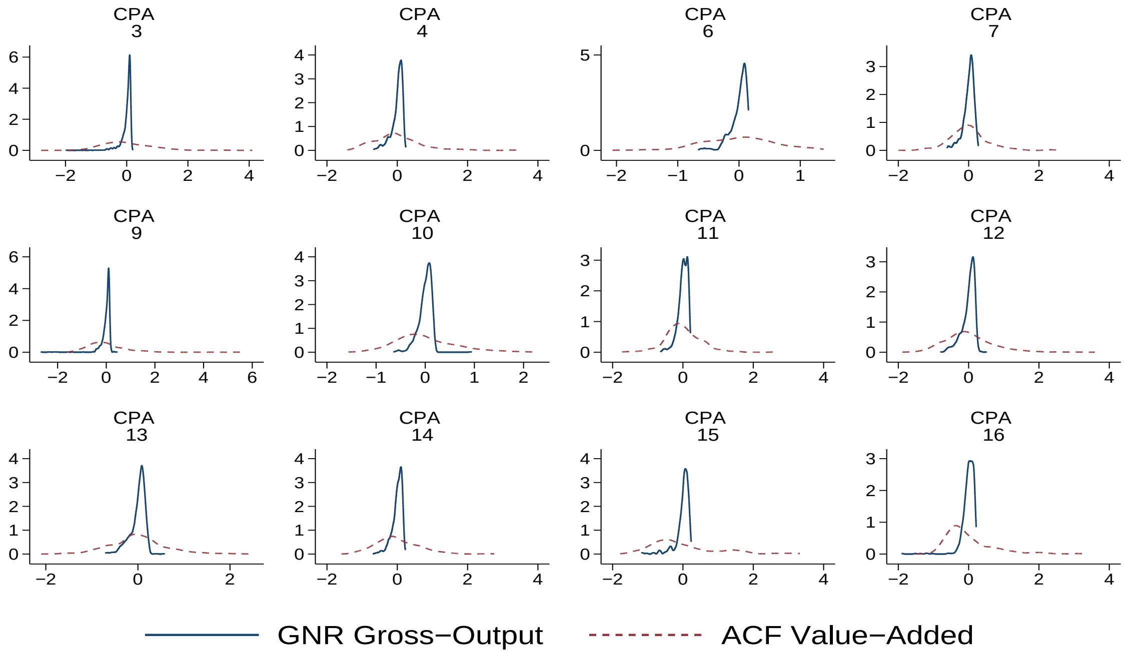
Source: Own calculations using GNR estimation procedure

Figure 4: Re-centered distribution of log TFP for manufacturing sector



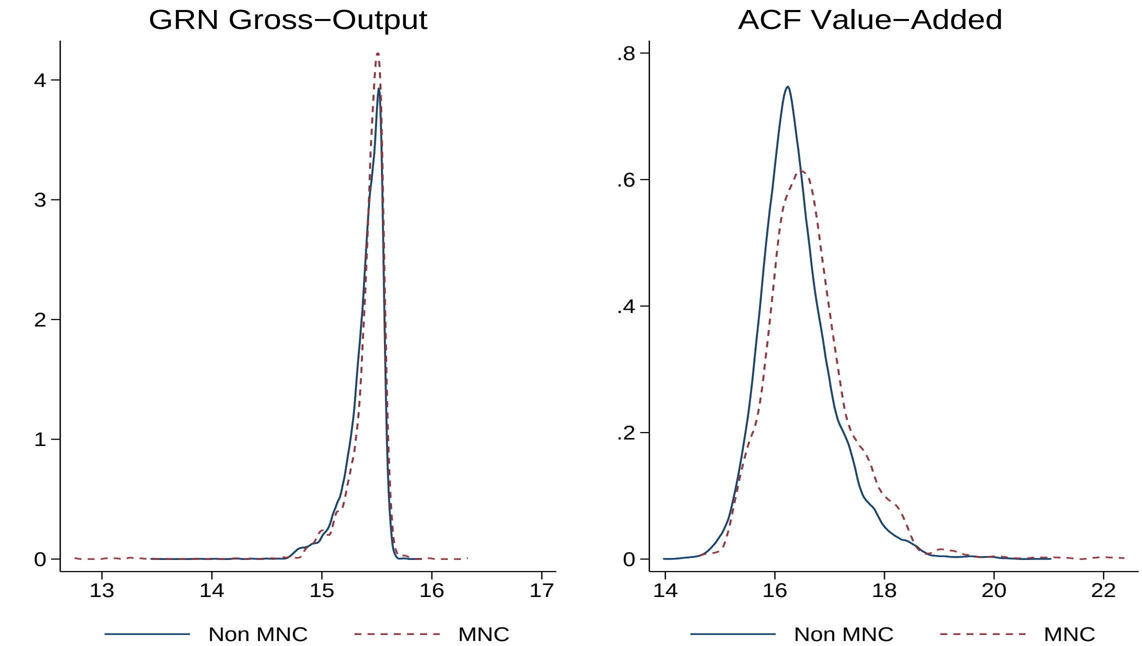
Source: Own calculations

Figure 5: Re-centered distribution of log TFP by CPA industries



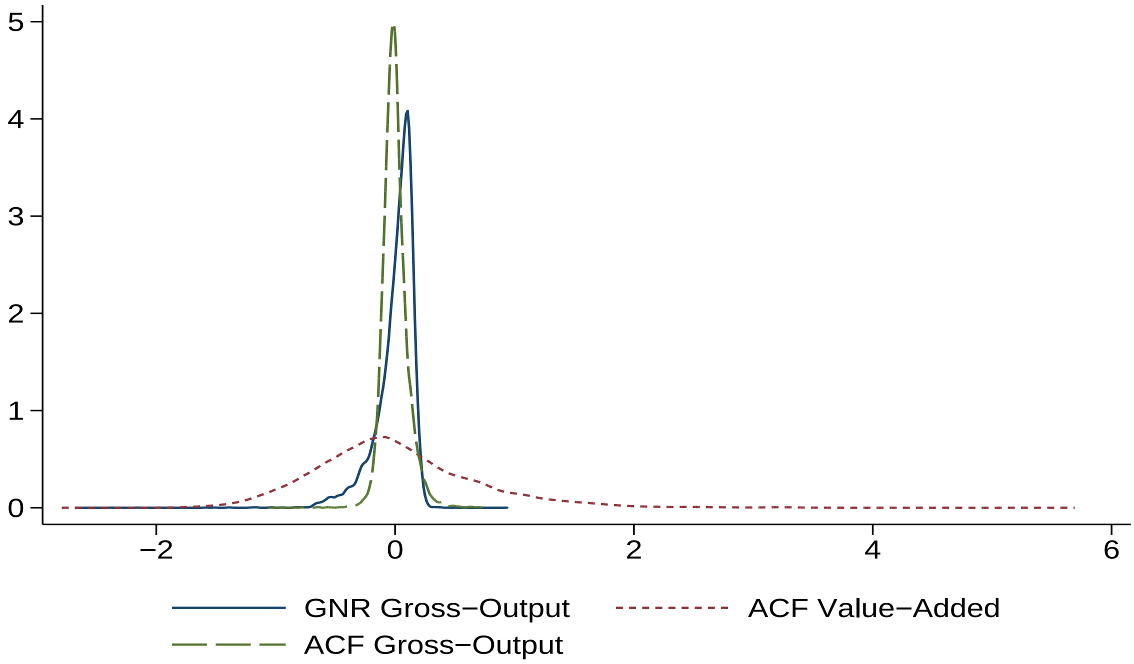
Source: Own calculations

Figure 6: Distribution of log TFP by MNC status for manufacturing sector



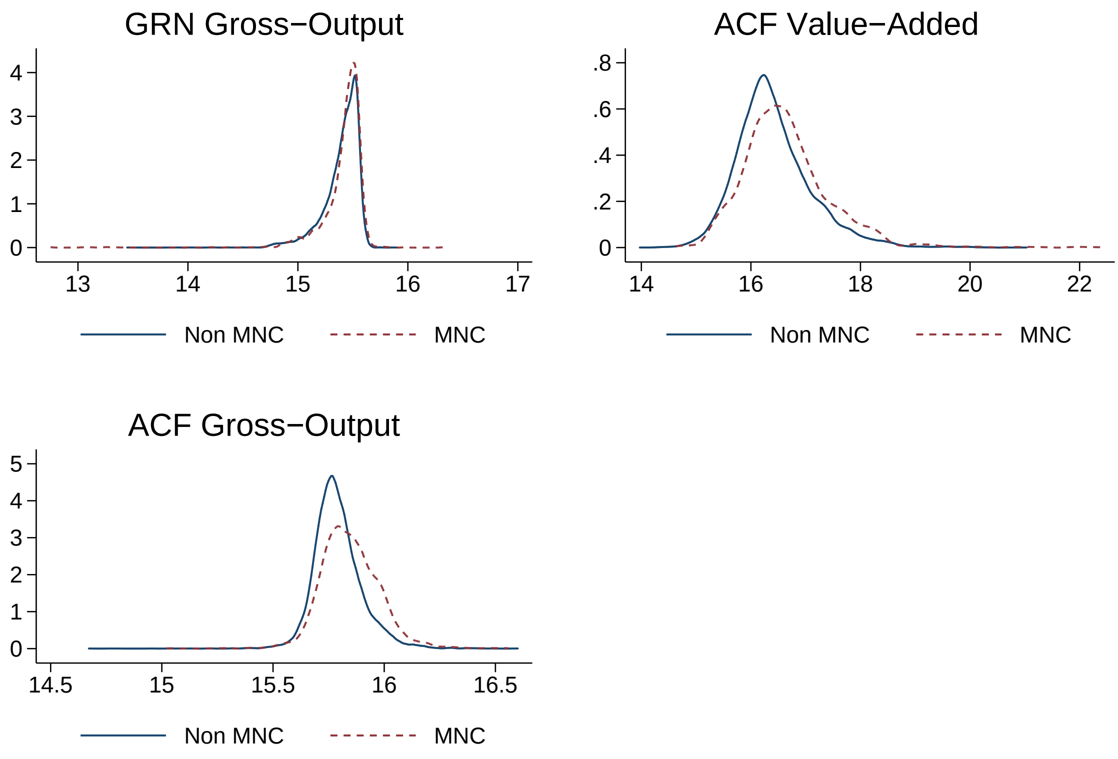
Source: Own calculations

Figure 7: Re-centered distribution of log TFP for manufacturing sector



Source: Own calculations

Figure 8: Distribution of log TFP 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
No 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 Euro.

Table 3: Inter-industry offshoring and inshoring proxies

	$Down\_off$	Up_off	$Down\_in$	Up_in	$Down\_off^{CN}$	Up_off^{CN}	$Down\_in^{CN}$	Up_in^{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 $Down\_off$, Up_off, $Down\_in$, Up_in, $Down\_off^{CN}$, Up_off^{CN}, $Down\_in^{CN}$ and Up_in^{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 D.(2007-2002) and D.(2006-2002) report the difference between 2007-2002 and 2006-2002 respectively.

Table 4: Output elasticities and returns to scale 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: $\hat{\theta}_k$, $\hat{\theta}_l$, $\hat{\theta}_m$ is the average, from all firms in each CPA industry, of the estimated output elasticities with respect to capital, labor and materials respectively. RTS stands for the average returns to scale. For both ACF Value-Added and ACF Gross-Output a translog production function is considered.

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 Fally (2011); Antràs et al. (2012) 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: TFP effects from inter-industry offshoring and inshoring

	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.921***	0.986***	0.933***
		(0.023)	(0.013)	(0.012)
$Down\_off_{t-1}$	-0.015	0.067***	0.109***	0.067***
	(0.012)	(0.010)	(0.012)	(0.012)
Up_off_{t-1}	-0.405***	-0.394***	-0.400***	-0.474***
	(0.093)	(0.062)	(0.109)	(0.067)
$Down\_in_{t-1}$	1.248***	0.571***	0.426**	0.561***
	(0.225)	(0.124)	(0.197)	(0.180)
Up_in_{t-1}	-0.684	6.356***	10.275***	6.161***
	(1.243)	(0.845)	(1.671)	(1.012)
SHH^{BE}_{t-1}	-0.017**	-0.001	-0.002	-0.000
	(0.007)	(0.002)	(0.004)	(0.001)
SUB^{BE}_{t-1}	0.009	-0.000	-0.004	0.001
	(0.008)	(0.001)	(0.005)	(0.004)
MNC_{t-1}	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: TFP effects from inter-industry offshoring and inshoring (High-Medium and Medium-Low Tech Industries)

	High-Medium Tech				Medium-Low Tech			
	FE	DFE	SGMM	One-Stage	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.908***	0.940***	0.927***		0.926***	0.996***	0.926***
		(0.016)	(0.019)	(0.017)		(0.018)	(0.006)	(0.020)
$Down\_off_{t-1}$	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)
Up_off_{t-1}	-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)
$Down\_in_{t-1}$	-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)
Up_in_{t-1}	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)
SHH_{t-1}^{BE}	-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)
SUB_{t-1}^{BE}	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)
MNC_{t-1}	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: TFP effects from inter-industry offshoring and inshoring (Capital and Labor Intensive Industries)

	Capital Intensive				Labor Intensive			
	FE	DFE	SGMM	One-Stage	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.935***	1.002***	0.950***		0.903***	0.961***	0.923***
		(0.011)	(0.004)	(0.015)		(0.028)	(0.020)	(0.015)
$Down\_off_{t-1}$	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)
Up_off_{t-1}	-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)
$Down\_in_{t-1}$	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)
Up_in_{t-1}	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)
SHH^{BE}_{t-1}	-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)
SUB^{BE}_{t-1}	-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)
MNC_{t-1}	-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: TFP effects from inter-industry offshoring and inshoring (Relatively Upstream and Downstream Industries)

	Relatively Upstream				Relatively Downstream			
	FE	DFE	SGMM	One-Stage	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.913***	0.992***	0.921***		0.927***	0.953***	0.936***
		(0.036)	(0.010)	(0.016)		(0.020)	(0.015)	(0.016)
$Down\_off_{t-1}$	-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)
Up_off_{t-1}	-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)
$Down\_in_{t-1}$	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)
Up_in_{t-1}	-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)
SHH^{BE}_{t-1}	-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)
SUB^{BE}_{t-1}	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)
MNC_{t-1}	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: TFP effects from inter-industry offshoring to and inshoring from China

	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.920***	0.970***	0.933***
		(0.023)	(0.016)	(0.014)
$Down\_off^{CN}_{t-1}$	-0.364	-0.429**	-0.354	-0.508
	(0.292)	(0.179)	(0.277)	(0.325)
$Up\_off^{CN}_{t-1}$	3.002**	3.240***	4.355***	4.121***
	(1.169)	(1.015)	(1.314)	(0.998)
$Down\_in^{CN}_{t-1}$	-142.645***	-4.161	14.421	-2.581
	(17.740)	(12.524)	(18.432)	(22.946)
$Up\_in^{CN}_{t-1}$	8.437	13.441	48.326*	13.376
	(18.413)	(20.466)	(27.079)	(37.138)
SHH^{BE}_{t-1}	-0.017**	-0.001	-0.004	-0.000
	(0.007)	(0.002)	(0.004)	(0.002)
SUB^{BE}_{t-1}	0.009	-0.000	-0.002	0.001
	(0.008)	(0.001)	(0.005)	(0.003)
MNC_{t-1}	0.003	0.002	0.000	0.000
	(0.009)	(0.002)	(0.007)	(0.004)
$Down\_off^{excCN}_{t-1}$	-0.109**	0.099**	0.229***	0.107**
	(0.055)	(0.040)	(0.075)	(0.042)
$Up\_off^excCN_{t-1}$	-0.756***	-0.596***	-0.499***	-0.757***
	(0.137)	(0.106)	(0.175)	(0.120)
$Down\_in^{excCN}_{t-1}$	2.737***	0.470**	0.317	0.414
	(0.304)	(0.195)	(0.293)	(0.357)
$Up\_in^{excCN}_{t-1}$	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: TFP effects from inter-industry offshoring to and inshoring from China (High-Medium and Medium-Low Tech Industries)

	High-Medium Tech				Medium-Low Tech			
	FE	DFE	SGMM	One-Stage	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.907***	0.963***	0.926***		0.926***	0.989***	0.926***
		(0.016)	(0.033)	(0.017)		(0.018)	(0.008)	(0.021)
$Down\_off_{t-1}^{CN}$	-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)
$Up\_off_{t-1}^{CN}$	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)
$Down\_in_{t-1}^{CN}$	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)
$Up\_in_{t-1}^{CN}$	-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)
SHH_{t-1}^{BE}	-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)
SUB_{t-1}^{BE}	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)
MNC_{t-1}	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)
$Down\_off_{t-1}^{excCN}$	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)
$Up\_off_{t-1}^{excCN}$	-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)
$Down\_in_{t-1}^{excCN}$	-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)
$Up\_in_{t-1}^{excCN}$	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: TFP effects from inter-industry offshoring to and inshoring from China (Capital and Labor Intensive Industries)

	Capital Intensive				Labor Intensive			
	FE	DFE	SGMM	One-Stage	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.934***	1.007***	0.949***		0.903***	0.927***	0.924***
		(0.011)	(0.006)	(0.017)		(0.028)	(0.021)	(0.017)
$Down\_off^{CN}_{t-1}$	-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)
$Up\_off^{CN}_{t-1}$	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)
$Down\_in^{CN}_{t-1}$	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)
$Up\_in^{CN}_{t-1}$	-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)
SHH^{BE}_{t-1}	-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)
SUB^{BE}_{t-1}	-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)
MNC_{t-1}	-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)
$Down\_off^{excCN}_{t-1}$	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)
$Up\_off^{excCN}_{t-1}$	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)
$Down\_in^{excCN}_{t-1}$	-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)
$Up\_in^{excCN}_{t-1}$	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: TFP effects from inter-industry offshoring to and inshoring from China (Relatively Upstream and Downstream Industries)

	Relatively Upstream				Relatively Downstream			
	FE	DFE	SGMM	One-Stage	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.912***	0.995***	0.920***		0.928***	0.957***	0.937***
		(0.036)	(0.010)	(0.017)		(0.020)	(0.013)	(0.013)
$Down\_off^{CN}_{t-1}$	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)
$Up\_off^{CN}_{t-1}$	-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)
$Down\_in^{CN}_{t-1}$	-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)
$Up\_in^{CN}_{t-1}$	-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)
SHH^{BE}_{t-1}	-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)
SUB^{BE}_{t-1}	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)
MNC_{t-1}	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)
$Down\_off^{excCN}_{t-1}$	-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)
$Up\_off^{excCN}_{t-1}$	-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)
$Down\_in^{excCN}_{t-1}$	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)
$Up\_in^{excCN}_{t-1}$	-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: TFP effects from inter-industry offshoring and inshoring using ACF with value-added production function

	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.938***	0.942***	0.946***
		(0.006)	(0.066)	(0.012)
$Down\_off_{t-1}$	-0.027	0.185***	0.252***	0.009
	(0.027)	(0.025)	(0.043)	(0.033)
Up_off_{t-1}	-0.838***	-0.917***	-1.073***	-0.097
	(0.268)	(0.181)	(0.364)	(0.202)
$Down\_in_{t-1}$	3.281***	0.761*	0.642	-0.262
	(0.995)	(0.442)	(0.717)	(0.450)
Up_in_{t-1}	-9.344***	15.028***	19.092***	2.602
	(3.387)	(2.413)	(5.449)	(2.605)
SHH^{BE}_{t-1}	-0.065***	-0.002	-0.021	-0.007
	(0.014)	(0.003)	(0.014)	(0.007)
SUB^{BE}_{t-1}	0.034*	0.001	-0.014	-0.004
	(0.018)	(0.003)	(0.014)	(0.011)
MNC_{t-1}	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 estimation procedure with value-added translog production function and are reported in parenthesis below point estimates.

Table 15: TFP effects from inter-industry offshoring to and inshoring from China using ACF with value-added production function

	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.935***	0.899***	0.946***
		(0.006)	(0.075)	(0.013)
$Down\_off^{CN}_{t-1}$	0.814	-0.456	-0.470	-0.124
	(0.728)	(0.383)	(0.819)	(0.597)
$Up\_off^{CN}_{t-1}$	8.439***	14.293***	20.444***	1.690
	(2.895)	(2.723)	(4.420)	(2.763)
$Down\_in^{CN}_{t-1}$	-654.059***	-285.791***	-2.770	-5.638
	(48.967)	(42.341)	(71.749)	(47.337)
$Up\_in^{CN}_{t-1}$	197.545***	198.529***	133.291	1.795
	(51.746)	(66.368)	(83.925)	(65.196)
SHH^{BE}_{t-1}	-0.065***	-0.002	-0.012	-0.007
	(0.014)	(0.003)	(0.014)	(0.006)
SUB^{BE}_{t-1}	0.033*	0.001	-0.015	-0.004
	(0.018)	(0.003)	(0.013)	(0.012)
MNC_{t-1}	0.106***	0.017***	0.022	0.010
	(0.025)	(0.005)	(0.022)	(0.007)
$Down\_off^{excCN}_{t-1}$	-0.698***	0.079	-0.176	-0.047
	(0.146)	(0.102)	(0.202)	(0.116)
$Up\_off^{excCN}_{t-1}$	-1.253***	-1.592***	-1.872***	-0.217
	(0.378)	(0.274)	(0.565)	(0.271)
$Down\_in^{excCN}_{t-1}$	10.613***	3.743***	0.398	-0.279
	(1.078)	(0.684)	(1.143)	(0.672)
$Up\_in^{excCN}_{t-1}$	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 estimation procedure with value-added translog production function and are reported in parenthesis below point estimates.

Table 16: TFP effects from inter-industry offshoring and in-shoring using ACF with gross-output production function

	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.889***	0.955***	0.905***
		(0.011)	(0.032)	(0.008)
$Down\_off_{t-1}$	0.000	0.080***	0.116***	0.004
	(0.012)	(0.010)	(0.022)	(0.006)
Up_off_{t-1}	-0.285***	-0.400***	-0.355**	-0.001
	(0.090)	(0.070)	(0.163)	(0.057)
$Down\_in_{t-1}$	0.758***	0.396**	0.519**	0.035
	(0.257)	(0.155)	(0.242)	(0.118)
Up_in_{t-1}	-2.495**	6.536***	10.436***	0.601
	(1.245)	(1.019)	(2.691)	(0.612)
SHH^{BE}_{t-1}	-0.020***	-0.001	-0.004	-0.003**
	(0.004)	(0.001)	(0.005)	(0.001)
SUB^{BE}_{t-1}	-0.001	-0.001	-0.003	-0.001
	(0.006)	(0.001)	(0.006)	(0.001)
MNC_{t-1}	0.025***	0.005***	0.009	0.003*
	(0.007)	(0.002)	(0.011)	(0.002)
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 estimation procedure with gross-output translog production function and are reported in parenthesis below point estimates.

Table 17: TFP effects from inter-industry offshoring to and inshoring from China using ACF with gross-output production function

	FE	DFE	SGMM	One-Stage
TFP_{t-1}		0.884***	0.965***	0.905***
		(0.011)	(0.042)	(0.008)
$Down\_off^{CN}_{t-1}$	0.492*	-0.278	-0.145	-0.097
	(0.279)	(0.180)	(0.316)	(0.125)
$Up\_off^{CN}_{t-1}$	3.113***	5.964***	3.924**	0.127
	(1.068)	(0.930)	(1.988)	(0.653)
$Down\_in^{CN}_{t-1}$	-296.989***	-114.415***	-34.749	16.810
	(19.180)	(16.092)	(26.810)	(15.306)
$Up\_in^{CN}_{t-1}$	82.535***	56.428**	88.033**	3.701
	(21.394)	(26.069)	(35.734)	(16.636)
SHH^{BE}_{t-1}	-0.020***	-0.001	-0.003	-0.003**
	(0.004)	(0.001)	(0.005)	(0.001)
SUB^{BE}_{t-1}	-0.001	-0.001	-0.004	-0.001
	(0.006)	(0.001)	(0.005)	(0.001)
MNC_{t-1}	0.026***	0.005***	0.007	0.003*
	(0.007)	(0.002)	(0.011)	(0.002)
$Down\_off^{excCN}_{t-1}$	-0.237***	0.027	0.137**	-0.044
	(0.051)	(0.040)	(0.069)	(0.027)
$Up\_off^{excCN}_{t-1}$	-0.375***	-0.710***	-0.245	-0.019
	(0.139)	(0.108)	(0.243)	(0.074)
$Down\_in^{excCN}_{t-1}$	4.180***	1.511***	0.881**	-0.191
	(0.330)	(0.254)	(0.359)	(0.186)
$Up\_in^{excCN}_{t-1}$	0.723	6.406***	6.450**	0.871
	(1.413)	(1.127)	(3.136)	(0.674)
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 estimation procedure with gross-output translog production function and are reported in parenthesis below point estimates.

Table 18: Robustness - Production function

	2ND	TR	CD
TFP_{t-1}	0.933***	0.947***	0.964***
	(0.012)	(0.009)	(0.007)
$Down\_off_{t-1}$	0.067***	0.070**	0.077**
	(0.012)	(0.035)	(0.030)
Up_off_{t-1}	-0.474***	-0.533**	-0.707***
	(0.067)	(0.208)	(0.241)
$Down\_in_{t-1}$	0.561***	0.294	0.062
	(0.180)	(0.607)	(0.560)
Up_in_{t-1}	6.161***	6.899***	9.142***
	(1.012)	(2.410)	(2.943)
TFP_{t-1}	0.933***	0.947***	0.964***
	(0.014)	(0.011)	(0.006)
$Down\_off^{CN}_{t-1}$	-0.508	-0.234	-0.323
	(0.325)	(0.629)	(0.691)
$Up\_off^{CN}_{t-1}$	4.121***	4.686	7.067***
	(0.998)	(4.232)	(2.676)
$Down\_in^{CN}_{t-1}$	-2.581	-32.246	-73.411
	(22.946)	(64.370)	(60.145)
$Up\_in^{CN}_{t-1}$	13.376	17.623	21.114
	(37.138)	(89.256)	(83.593)
Observations	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. 2ND refer to the order of the polynomial used for both the output elasticity of the flexible input and constant of integration in the GNR procedure. TR and CD refer to Translog and Cobb-Douglas production functions respectively. Each panel represents a separate regression.

Table 19: Robustness - Including intra-industry proxies

	No intra-industry	With intra-industry
TFP_{t-1}	0.933***	0.934***
	(0.012)	(0.011)
$Down\_off_{t-1}$	0.067***	0.060***
	(0.012)	(0.012)
Up_off_{t-1}	-0.474***	-0.375***
	(0.067)	(0.084)
$Down\_in_{t-1}$	0.561***	0.575***
	(0.180)	(0.193)
Up_in_{t-1}	6.161***	4.805***
	(1.012)	(1.028)
off_{t-1}		0.018
		(0.056)
in_{t-1}		0.055
		(0.038)
TFP_{t-1}	0.933***	0.933***
	(0.014)	(0.011)
$Down\_off_{t-1}^{CN}$	-0.508	-0.526**
	(0.325)	(0.247)
$Up\_in_{t-1}^{CN}$	4.121***	3.410**
	(0.998)	(1.361)
$Down\_off_{t-1}^{CN}$	-2.581	-3.557
	(22.946)	(24.310)
$Up\_in_{t-1}^{CN}$	13.376	26.928
	(37.138)	(28.229)
off_{t-1}		0.053
		(0.049)
in_{t-1}		-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. Each panel represents a separate regression.

Table 20: Robustness - Proxies

	fix2000	fix2001	fix2002	Varying
TFP_{t-1}	0.933***	0.934***	0.933***	0.933***
	(0.012)	(0.013)	(0.012)	(0.013)
$Down\_off_{t-1}$	0.067***	0.067***	0.066***	0.057***
	(0.012)	(0.008)	(0.010)	(0.009)
Up_off_{t-1}	-0.474***	-0.477***	-0.450***	-0.189*
	(0.067)	(0.081)	(0.064)	(0.100)
$Down\_in_{t-1}$	0.561***	0.616***	0.553***	0.486***
	(0.180)	(0.188)	(0.174)	(0.174)
Up_in_{t-1}	6.161***	5.668***	5.586***	1.540***
	(1.012)	(0.787)	(0.649)	(0.518)
TFP_{t-1}	0.933***	0.933***	0.933***	0.933***
	(0.014)	(0.011)	(0.013)	(0.013)
$Down\_off^{CN}_{t-1}$	-0.508	-0.512*	-0.520**	-0.346*
	(0.325)	(0.294)	(0.259)	(0.181)
$Up\_off^{CN}_{t-1}$	4.121***	4.128***	3.890***	4.504***
	(0.998)	(0.931)	(0.988)	(1.311)
$Down\_in^{CN}_{t-1}$	-2.581	1.205	10.137	2.158
	(22.946)	(19.281)	(19.297)	(18.729)
$Up\_in^{CN}_{t-1}$	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. fix2000, fix2001, fix2002 and varying refer to proxies where the technical coefficients of proxies are fixed at values in year 2000, 2001, 2002 and varying over time respectively. Each panel represents a separate regression.

Table 21: Robustness - Trimming sample

	10%	5%	15%	20%	0%
TFP_{t-1}	0.933***	0.939***	0.931***	0.838***	0.981***
	(0.012)	(0.025)	(0.007)	(0.013)	(0.032)
$Down\_off_{t-1}$	0.067***	0.066***	0.066***	0.057**	0.044*
	(0.012)	(0.023)	(0.008)	(0.023)	(0.025)
Up_off_{t-1}	-0.474***	-0.455***	-0.478***	-0.416***	-0.869***
	(0.067)	(0.099)	(0.059)	(0.077)	(0.196)
$Down\_in_{t-1}$	0.561***	0.594*	0.585***	0.620**	-0.711
	(0.180)	(0.312)	(0.122)	(0.312)	(1.187)
Up_in_{t-1}	6.161***	4.885***	6.587***	6.727***	6.522**
	(1.012)	(1.149)	(0.863)	(0.707)	(2.861)
TFP_{t-1}	0.933***	0.938***	0.930***	0.838***	0.981***
	(0.014)	(0.026)	(0.007)	(0.013)	(0.031)
$Down\_off^{CN}_{t-1}$	-0.508	-0.379	-0.487**	-0.203	-1.183**
	(0.325)	(0.378)	(0.190)	(0.372)	(0.570)
$Up\_off^{CN}_{t-1}$	4.121***	4.414**	4.222***	3.895***	-1.816
	(0.998)	(2.071)	(0.803)	(0.860)	(2.680)
$Down\_in^{CN}_{t-1}$	-2.581	-4.226	-5.695	-9.906	7.613
	(22.946)	(25.998)	(15.969)	(40.184)	(53.648)
$Up\_in^{CN}_{t-1}$	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. 10%, 5%, 15%, 20% and 0% represent the $(1 - \#\%)$ percentile respectively of the chi-squared distribution used as a threshold to separate outliers from non-outliers using the Bacon process proposed by Billor et al. (2000). Each panel represents a separate regression.

Table 22: Robustness - Labor adjustment frictions

	Adj. lag	Adj. costs
TFP_{t-1}	0.933***	0.933***
	(0.012)	(0.010)
$Down\_off_{t-1}$	0.067***	0.067***
	(0.012)	(0.008)
Up_off_{t-1}	-0.474***	-0.474***
	(0.067)	(0.062)
$Down\_in_{t-1}$	0.561***	0.561***
	(0.180)	(0.182)
Up_in_{t-1}	6.161***	6.161***
	(1.012)	(0.737)
TFP_{t-1}	0.933***	0.933***
	(0.014)	(0.009)
$Down\_off^{CN}_{t-1}$	-0.508	-0.508**
	(0.325)	(0.204)
$Up\_off^{CN}_{t-1}$	4.121***	4.120***
	(0.998)	(0.793)
$Down\_in^{CN}_{t-1}$	-2.581	-2.596
	(22.946)	(19.471)
$Up\_in^{CN}_{t-1}$	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. Adj. lag refers to an adjustment lag in labor which is assumed to be a dynamic input chosen one year before the productivity realisation. Adj. costs refers to the case where labor is a flexible input but subject to adjustment costs, i.e firing and hiring costs, and therefore use one lag of labor input as instrument in the second step of the GNR procedure. Each panel represents a separate regression.

Table 23: Robustness - Firm fixed effects

	No Firm FE	Firm FE-l1	Firm FE-l2
TFP_{t-1}	0.933***	-0.039	-0.036
	(0.012)	(0.076)	(0.081)
$Down\_off_{t-1}$	0.067***	0.053*	0.053*
	(0.012)	(0.027)	(0.028)
Up_off_{t-1}	-0.474***	-0.510**	-0.514***
	(0.067)	(0.204)	(0.186)
$Down\_in_{t-1}$	0.561***	1.169***	1.164*
	(0.180)	(0.433)	(0.645)
Up_in_{t-1}	6.161***	3.735	3.717
	(1.012)	(3.642)	(3.506)
TFP_{t-1}	0.933***	-0.041	-0.039
	(0.014)	(0.073)	(0.065)
$Down\_off^{CN}_{t-1}$	-0.508	-0.090	-0.070
	(0.325)	(0.956)	(0.920)
$Up\_off^{CN}_{t-1}$	4.121***	4.406*	4.392
	(0.998)	(2.269)	(2.876)
$Down\_in^{CN}_{t-1}$	-2.581	-57.529*	-57.823
	(22.946)	(29.933)	(39.869)
$Up\_in^{CN}_{t-1}$	13.376	56.340	56.335
	(37.138)	(53.852)	(50.115)
Observations	12731	9966	9966

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. Firm FE-l1 and Firm FE-l2 refer to the augmented GNR procedure accounting for firm fixed effects, where in the 2nd step we identify the augmented first differenced equation using one and two lags of the baseline instrument set respectively. Each panel represents a separate regression.

Table 24: Robustness - Imperfect competition in output market

	PC	IC
TFP_{t-1}	0.933***	0.930***
	(0.012)	(0.015)
$Down\_off_{t-1}$	0.067***	0.061***
	(0.012)	(0.013)
Up_off_{t-1}	-0.474***	-0.388***
	(0.067)	(0.106)
$Down\_in_{t-1}$	0.561***	0.432*
	(0.180)	(0.247)
Up_in_{t-1}	6.161***	5.464***
	(1.012)	(1.022)
TFP_{t-1}	0.933***	0.930***
	(0.014)	(0.017)
$Down\_off^{CN}_{t-1}$	-0.508	-0.551*
	(0.325)	(0.291)
$Up\_off^{CN}_{t-1}$	4.121***	2.352**
	(0.998)	(0.977)
$Down\_in^{CN}_{t-1}$	-2.581	17.536
	(22.946)	(27.354)
$Up\_in^{CN}_{t-1}$	13.376	14.954
	(37.138)	(46.642)
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. PC and IC refer to perfect and imperfect competition in the output market respectively. Each panel represents a separate regression.